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Introduction to the content and purpose of the book.

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- **Tinkering with Twitter's API** : Exploring Twitter's API to access and interact with tweet data.
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- **Visualizing Tweet Graphs** : Creating visual representations of tweet interactions.
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- **Closing Remarks** : Final thoughts on working with Twitter data.

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3. Mailboxes: Oldies but Goodies

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- **mbox + CouchDB = Relaxed Email Analysis** : Integrating mbox with CouchDB for email insights.
- **Bulk Loading Documents into CouchDB** : Methods for efficiently adding documents to CouchDB.
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This outline provides a structured overview of the content, focusing on key concepts and techniques for working with Twitter data, microformats, and email analysis.

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Visualizing Mail Events with SIMILE Timeline

- **SIMILE Timeline** : A tool for visualizing email events chronologically.
- **Analyzing Your Own Mail Data** : Techniques to examine personal email data for insights.
- **The Graph Your (Gmail) Inbox Chrome Extension** : A tool for creating visual representations of Gmail inbox data.
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4. Twitter: Friends, Followers, and Setwise Operations

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- **Redis: A Data Structures Server** : Utilizing Redis for managing Twitter data.
- **Elementary Set Operations** : Basic operations for analyzing sets of friends/followers.
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- **Calculating Similarity by Computing Common Friends and Followers** : Methods for assessing similarity among users based on mutual connections.
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5. Twitter: The Tweet, the Whole Tweet, and Nothing but the Tweet

- **Pen : Sword :: Tweet : Machine Gun** : Metaphorical comparison of tweets to powerful communication tools.
- **Analyzing Tweets (One Entity at a Time)** : Focused analysis of individual tweets.
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- **Visualizing Tons of Tweets** : Techniques for visualizing large volumes of tweet data.
- **Visualizing Tweets with Tag Clouds** : Creating tag clouds to represent tweet content.
- **Visualizing Community Structures in Twitter Search Results** : Analyzing the community dynamics within Twitter search results.
- **Closing Remarks** : Concluding thoughts on tweet analysis.

6. LinkedIn: Clustering Your Professional Network for Fun (and Profit?)

- **Motivation for Clustering** : Reasons to analyze and group LinkedIn connections for networking and business opportunities.

This summary outlines the key topics related to email and Twitter data visualization and analysis, emphasizing important concepts and

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Clustering Contacts by Job Title

- **Standardizing and Counting Job Titles** : Process of normalizing job titles to ensure consistency in data analysis.
- **Common Similarity Metrics for Clustering** : Metrics like Jaccard index or cosine similarity used to determine how similar job titles are for effective clustering.
- **A Greedy Approach to Clustering** : Strategy that iteratively groups contacts based on the most immediate benefits, optimizing local choices.
- **Hierarchical and k-Means Clustering** :
 - **Hierarchical Clustering** : Builds a tree of clusters, allowing exploration of data at multiple levels.
 - **k-Means Clustering** : Partitions data into k distinct clusters based on feature similarity.
- **Fetching Extended Profile Information** : Techniques to gather additional data about contacts to improve clustering accuracy.
- **Geographically Clustering Your Network** : Grouping contacts based on their geographical locations to analyze regional networks.
- **Mapping Your Professional Network with Google Earth** : Visualizing contact data using Google Earth to understand geographical relationships.
- **Mapping Your Professional Network with Dorling Cartograms** : Using visual representations to depict the size of clusters based on job titles or roles.
- **Closing Remarks** : Summary of the benefits of clustering contacts for professional networking.

7. Google Buzz: TF-IDF, Cosine Similarity, and Collocations

- **Buzz = Twitter + Blogs** : Overview of Google Buzz as a hybrid social platform.
- **Data Hacking with NLTK** : Utilizing the Natural Language Toolkit (NLTK) for text processing and analysis.
- **Text Mining Fundamentals** : Basics of extracting valuable insights from text data.
- **A Whiz-Bang Introduction to TF-IDF** : Explaining the **Term Frequency-Inverse Document Frequency (TF-**

IDF) method for measuring word importance in documents.

- **Querying Buzz Data with TF-IDF** : Using TF-IDF to analyze and retrieve relevant Buzz data.
- **Finding Similar Documents** : Techniques for identifying documents with similar content based on TF-IDF.
- **The Theory Behind Vector Space Models and Cosine Similarity** :
 - **Vector Space Models** : Representing text as vectors for mathematical analysis.
 - **Cosine Similarity** : A measure of similarity between two non-zero vectors based on the cosine of the angle between them.
- **Clustering Posts with Cosine Similarity** : Grouping posts by measuring how similar they are to each other.
- **Visualizing Similarity with Graph Visualizations** : Using graphs to represent relationships and similarities among documents.
- **Buzzing on Bigrams** : Analyzing two-word combinations (bigrams) for deeper insights.
- **Collocation Analysis** : Using **contingency tables** and scoring functions to understand word relationships.
- **Tapping into Your Gmail** : Techniques for extracting data from Gmail for analysis.
- **Accessing Gmail with OAuth** : Ensuring secure access to Gmail accounts using OAuth authentication.
- **Fetching and Parsing Email Messages** : Methods for retrieving and processing email data.
- **Before You Go Off and Try to Build a Search Engine...** : Considerations and challenges before developing a search engine.
- **Closing Remarks** : Final thoughts on leveraging Buzz data for insights.

8. Blogs et al.: Natural Language Processing (and Beyond)

- **NLP: A Pareto-Like Introduction** : Overview of Natural Language Processing (NLP) principles and applications.
- **Syntax and Semantics** : Distinction between sentence structure (syntax) and meaning (semantics).
- **A Brief Thought Exercise** : Engaging exercises to think critically about NLP.
- **A Typical NLP Pipeline with NLTK** : Step-by-step process of NLP tasks using NLTK.
- **Sentence Detection in Blogs with NLTK** : Techniques for identifying sentences in blog texts.
- **Summarizing Documents** : Methods for condensing documents into concise summaries.
- **Analysis of Luhn's Summarization Algorithm** : Examination of Luhn's algorithm for summarizing texts.
- **Entity-Centric Analysis** : Focusing on specific entities within text for detailed analysis.
- **Quality of Analytics** : Evaluating the effectiveness and accuracy of NLP analytics.
- **Closing Remarks** : Summary of NLP's role in text analysis and its future potential.

9. Facebook: The All-in-One Wonder

- **Tapping into Your Social Network Data** : Methods to access and analyze your personal data from Facebook.
- **From Zero to Access Token in Under 10 Minutes** : Quick guide on obtaining an access token for Facebook's APIs, necessary for data retrieval.
- **Facebook's Query APIs** : Overview of the APIs available for querying and manipulating Facebook data, enabling developers to extract specific information.
- **Visualizing Facebook Data** : Techniques and tools for creating visual representations of Facebook data to understand social connections better.
- **Visualizing Your Entire Social Network** : Methods to map out and analyze all your Facebook connections.
- **Visualizing Mutual Friendships Within Groups** : Analyzing friendships and connections specifically within user-created groups for insights on social dynamics.
- **Where Have My Friends All Gone? (A Data-Driven Game)** : Engaging with your data through a game format that explores changes in your friend network.
- **Visualizing Wall Data As a (Rotating) Tag Cloud** : Creating dynamic tag clouds to represent interactions on your Facebook wall, highlighting popular topics and discussions.

- **Closing Remarks** : Summary of the importance and potential of leveraging Facebook data for insights and understanding social networks.

10. The Semantic Web: A Cocktail Discussion

- **An Evolutionary Revolution?** : Discussing the transformative potential of the Semantic Web in organizing and interpreting data on the internet.
- **Man Cannot Live on Facts Alone** : Emphasizing that raw data needs context and understanding for meaningful use.
- **Open-World Versus Closed-World Assumptions** : Differentiating between assumptions in knowledge representation; open-world allows for incomplete information, while closed-world assumes all relevant facts are known.
- **Inferencing About an Open World with FuXi** : Exploring FuXi, a framework for reasoning about data in an open-world scenario, facilitating deeper insights.
- **Hope** : Concluding thoughts on the future possibilities.

Preface

- **The Web as a Social Creation** : Tim Berners-Lee emphasizes that the **Web** is primarily designed for social interaction rather than just technical purposes. Its goal is to enhance human connections and collaboration across distances.
- **Audience** : This book targets readers with a **basic programming background** who are interested in **data mining** and **analysis** of social web data.
- **Structure and Length** :
 - The chapters are intentionally **short**, which may leave readers wanting more detail. This brevity is necessary due to the rapidly evolving nature of the topic.
 - The author follows the **80-20 rule**, focusing on the most critical 20% of information that provides 80% of the value.
- **Content Overview** :
 - The book offers a balance of **breadth and depth**. While it covers many topics, some chapters dive deeper into complex **mining and analysis techniques**.
 - Readers can choose to read it **cover to cover** for a comprehensive overview or select specific chapters of interest, as each chapter is designed to stand alone while maintaining

Social Networking and the Shift to Mainstream

- **Evolution of Social Networks** : Websites like **Facebook** , **Twitter** , and **LinkedIn** have transformed from trends to major global platforms. By the first quarter of 2010, Facebook overtook Google in **page visits** , signaling a change in how people engage online.
- **Social vs. Research Tool** : While it's debatable whether the Web is now more social than informational, the rise of social networks indicates they fulfill basic human needs in ways search engines do not.
- **Impact on Daily Life** : Social networks are reshaping how we live both online and offline, bridging the gap between real life and cyberspace, highlighting both positive and negative aspects of technology.

Key Questions Explored in the Book

The book addresses essential questions related to social networks and data analysis:

- **Connections** : Who knows whom, and what mutual friends exist?
- **Communication Frequency** : How often do certain individuals communicate?
- **Communication Symmetry** : Is the communication between individuals balanced?
- **Activity Levels** : Who are the quietest or most talkative users in a network?
- **Influence and Popularity** : Who are the most influential or popular figures within a network?
- **Topics of Interest** : What discussions are taking place, and are they engaging?

Analytical Approaches

- The answers to these questions help illustrate connections and provide context for relationships within networks.
- This initial analytical work sets the stage for more advanced processes. The availability of **social networking APIs** and **open-source toolkits** makes starting this analysis accessible.

Graph-Centric Perspective

- The book views the **social web** as a graph composed of people, activities, events, and concepts.
- Companies like Google and Facebook are shifting from **web-centric** to **graph-centric** terminology, emphasizing the interconnectedness of data.
- Tim Berners-Lee proposed the term **Web 2.0**

The Vision of the Web and Its Evolution

- **Tim Berners-Lee's Vision** : It's uncertain if Berners-Lee's original vision for the Web will be fully realized, but the Web is increasingly enriched with **social data** . Over time, the **gap** between social web dynamics and a **semantic web** is narrowing, suggesting that social interactions are vital for the web's evolution.

What to Expect from This Book

- **Scope Limitations** : This book does not cover advanced topics like building a **natural language processor** or cutting-edge visualization techniques. If you're looking for comprehensive guides on these subjects, you may find it lacking.
- **Practical Solutions** : Despite its brevity, the book aims to provide reasonable solutions to complex problems related to the **social web** , allowing for enjoyable and practical applications of data analysis.

Intended Audience and Usage

- **Active Internet Connection Required** : The book assumes that readers are connected to the Internet. It contains numerous **hyperlinks** and code examples linked to **GitHub** , making it unsuitable for offline reading.
- **Collaborative Coding** : Readers are encouraged to engage with the code examples on GitHub, fostering collaboration and allowing for the extension and improvement of shared projects.
- **Not for Distributed Computing** : This book does not focus on distributed computing platforms like **Hadoop** or **Cassandra** . While it touches on technologies like **CouchDB** and **Redis** , these are used in a specific context rather than as comprehensive guides.

Resources

- **GitHub Repository** : The latest code and updates can be found at <http://github.com/ptwobrussell/Mining-the-Social-Web>.
- **Social Media** : Follow the book's developments on Twitter @SocialWebMining.

Key Considerations for Data Projects

- **Transitioning to Distributed Systems :**

- While examples in this book are designed for a **single machine** , they can be adapted for **distributed technologies** if you need **horizontal scalability** .
- **Recommendation** : Start by mastering the fundamentals in a simpler environment before migrating to a more complex distributed system. Be prepared to adjust your algorithms for performance when data access is no longer local.
- **Tool Suggestion** : Consider using **Dumbo** for distributed processing. Follow the book's Twitter account (@SocialWebMining) for extended examples involving Dumbo.

Legal and Ethical Considerations

- **Data Usage Compliance :**

- This book does not provide legal advice regarding data from social networking sites, but it aims to comply with the terms of these platforms.
- Many social networking sites have restrictive licensing terms, treating their data as **walled gardens** to protect user privacy and maintain their business value.

Technical Environment

- **Preferred Environment :**

- The book favors a **nix environment** (Linux/Unix). Some visualizations may have issues on **Windows** , but alternatives or workarounds will be suggested when necessary. You can usually bypass these sections without significant loss of understanding.

Tools and Prerequisites

- **Learning Requirements :**

- Motivation to learn **Python** and engage with social data is essential. No prior knowledge in areas like data analysis, high-performance computing, or machine learning is required.
- Some examples may introduce concepts like **thread pools** , but Python's **intuitive syntax** and rich ecosystem make it an accessible choice for beginners.

- **Python Advantages :**

- Python's core data structures are similar to **JSON** , making it suitable for data manipulation tasks. Advanced tasks, such as **natural language processing** , will also be covered with easy-to-use packages.

Programming Approach and Language Choice

- **Application Programming Focus :**

- This book emphasizes using technology from an **application programmer** perspective. The code examples

can likely be adapted to other programming languages easily.

- **GitHub Collaboration** : The aim is for readers to contribute similar code adaptations on **GitHub** .
- **Python as a Tool** :
 - No justification is needed for using **Python** ; it's an excellent choice for the tasks at hand. If you're new to Python, a quick review of the syntax will confirm its suitability.
 - **Resources** : Excellent documentation is available online, with the official **Python tutorial** being a recommended starting point.

Visualization Techniques

- **Diverse Visualizations** :
 - The book covers various **visualization tools** ranging from common software like **spreadsheets** to advanced options like **Graphviz** and modern HTML5 technologies such as **Protovis** .
 - Each chapter introduces new visualizations that build logically on previous material, promoting the creation of **lightweight prototypes** .
- **Prototype Development** :
 - Most visualizations are slight adaptations of existing examples, making it easier for learners to understand and build upon the material.

Typographical Conventions

- **Italic** : Used for new terms, URLs, email addresses, filenames, and file extensions.
- **Constant Width** : Indicates program code, including variable names, function names, databases, and keywords.
- **Constant Width Bold** : Represents commands or text to be typed exactly as shown, also used for emphasis.
- **Constant Width Italic** : Denotes text that should be replaced with user-specific values.
- **Tip Icon** : Indicates tips, suggestions, or general notes throughout the text.

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Warning Icon

- This icon is used to indicate **warnings or cautions** within the text.

Using Code Examples

- **Availability** : Most numbered code examples from the book can be downloaded from the official GitHub repository: [GitHub - Mining the Social Web](#).
- **Updates** : Monitor this repository for the latest bug fixes and extended examples contributed by the author and the coding community.

Code Usage Permissions

- **General Use** : You can use the code from the book in your programs and documentation without needing permission.
 - Example: Writing a program that includes multiple code snippets from the book is allowed.
- **Special Cases** :
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- **Philosophy** : The author believes that personal and professional growth is a collective journey, and credits those who supported him along the way.

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- **Overall Appreciation** : Acknowledges the impact of many others who have shaped both the author's life and the book's outcome.
- **Reader Engagement** : The author thanks readers for considering the book. While acknowledging that some errors may exist, he believes it will be

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Chapter 1: Introduction to Hacking on Twitter Data

- **Overview** : This chapter introduces the process of collecting and analyzing social web data, specifically focusing on Twitter. Instead of discussing APIs or design principles in detail, it provides quick, practical examples to motivate readers.

Setting Up the Development Environment

- **Python as the Primary Language** : The examples in this book use **Python** . If you already have a recent version installed with **easy install** , you can skip the setup instructions.
- **Installing Python** :
 - If you don't have Python, now is the time to learn it, as it's user-friendly.
 - Download Python from python.org.
 - **Windows Users** : It's recommended to install **ActivePython** . This version:
 - Automatically adds Python to your system path for easy access in the terminal.
 - Includes **easy install** , which will be useful later.
- **Python Version** : The book focuses on Python **2.7** . While it should work with newer versions, Python 2.7 is still widely used in the community, so stick with it unless you're sure all dependencies are compatible with Python 3.
- **Testing the Installation** : After installation, you can verify that Python is set up correctly by typing `python` in the terminal, which will launch the Python interpreter.

This chapter aims to provide a quick start into the world of social data analysis using Twitter, setting the stage for deeper exploration in later chapters.

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Example 1-1: First Python Interpreter Session

- **Basic Python Commands** :
 - **Print Statement** : python Copy code `>>> print "Hello World"` Hello World
 - **Comments** : Use `#` to add comments in the code. python Copy code `>>> # this is a comment`
 - **For Loop** : Iterates through a range of numbers (0 to 9). python Copy code `>>> for i in range (0 , 10):` # a loop ... `print i,` # the comma suppresses line breaks ... 0 1 2 3 4 5 6 7 8 9
 - **List Comprehension** : Creates a list of numbers from 0 to 9. python Copy code `>>> numbers = [i for i in range (0 , 10)]` # a list comprehension `>>> print numbers` [0 , 1 , 2 , 3 , 4 , 5 , 6 , 7 , 8 , 9]
 - **Conditional Logic** : Checks if a number is in the list and prints the result. python Copy code `>>> if 10 in numbers:` # conditional logic ... `print True` ... `else :` ... `print False` ... False

Easy install

- **What is `easy_install` ?** : A package manager for Python that simplifies the installation of Python packages. It eliminates the need to manually download, build, and install packages from source.
- **Installation :**
 - Download from [Python Package Index](#).
 - For *nix users, use `sudo easy_install` to write to global directories.
 - Windows users should install **ActivePython** , which includes `easy_install` by default.
- **Common Issues :** Windows users might encounter problems related to compiling C code when using `easy_install` . It's beneficial to read the blog post titled "Installing `easy_install` ...could be easier" for troubleshooting.

Installing Packages

- **Installing NetworkX :** This package is essential for building and analyzing graphs, which will be used throughout the book.

 bash Copy code \$ `easy_install networkx` Searching for networkx ...truncated output... Finished processing dependencies for networkx
- **Note on `pip` :** While `easy_install` is used in this book, the Python com

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Importing NetworkX and Handling Dependencies

- **Installing NetworkX :** After installation, you may encounter an **ImportError** when trying to import it.
 python Copy code >>> `import networkx` Traceback (most recent call last): ... truncated output ...
 ImportError: No module named numpy
- **Understanding ImportError :** This error indicates that a required package, in this case, **numpy** , is missing. Numpy is crucial for scientific computing and is a dependency of NetworkX.
- **Fixing the ImportError :**
 - Close the Python interpreter.
 - Install the missing dependency using: bash Copy code \$ `easy_install numpy`
 - After installation, you can open a new interpreter session and import NetworkX successfully.

Example 1-2: Creating a Graph with NetworkX

- **Creating a Graph :**
 python Copy code >>> `import networkx` >>> `g = networkx.Graph()` # Initialize a new graph >>> `g.add`
`edge (1 , 2)` # Add an edge between nodes 1 and 2 >>> `g.add` `node ("spam")` # Add a new node
 labeled "spam" >>> `print g.nodes()` # Print all nodes [1 , 2 , 'spam'] >>> `print g.edges()` #
 Print all edges [(1 , 2)]

- **Outcome** : You've successfully created a graph with nodes and edges, establishing a foundation for further data manipulation and analysis.

Next Steps

- **Review Python Fundamentals** : If you're new to Python or need a refresher, consider reviewing the **official Python tutorial** online before moving on to more complex tasks.

Collecting and Manipulating Twitter Data

- **Overview of Twitter** : Twitter is a **real-time microblogging service** that allows users to post short messages called **tweets** , limited to 140 characters.
- **Network Structure** : Unlike platforms like Facebook or LinkedIn, Twitter has an **asymmetric network** structure characterized by "friends" and "followers." This means that one user can follow another without requiring mutual agreement.

This sets the stage for understanding how to work with Twitter

Understanding Twitter Accounts and User Dynamics

- **Twitter Structure** :
 - **Friends** : Accounts you choose to follow.
 - **Followers** : Accounts that follow you.
 - **Home Timeline** : Displays tweets only from accounts you follow, which you curate based on interest.
- **Importance of Twitter** :
 - **User Base** : Twitter has an extensive number of users, making it significant for social interaction.
 - **Marketing Tool** : It's widely used for marketing and as a communication platform for third-party messaging services.
 - **APIs** : Twitter provides a rich set of APIs that allow for various interactions and data mining, enhancing its utility.
- **Getting Started** :
 - Before heavy development, review Twitter's **terms of service** , **API documentation** , and **API rules** to understand what is permissible with Twitter data.
 - The book assumes you have a Twitter account with sufficient friends and followers for data exploration.

Tinkering with Twitter's API

- **Using the Twitter Package :**

- Install the package using: bash Copy code `$ easy_install twitter`
- This package includes a command-line utility and an IRC bot. You can access the command-line utility by typing `twitter` in the shell.

- **Interactive Python Work :**

- The focus will be on using the Twitter API within the **interactive Python interpreter** .
- You can explore documentation using:
 - For *nix users: bash Copy code `$ pydoc twitter.Twitter`
 - For Windows users: bash Copy code `$ python -mpydoc twitter.Twitter`

- **Accessing Help :**

- You can also type `help(twitter.Twitter)` in the interpreter for inline documentation.

- **Documentation Tips :**

- If you frequently consult module documentation, consider using the `-w` option with `pydoc` to write an HTML page that you can save and bookmark for easy access.

This foundational knowledge prepares you to effectively utilize Twitter's API for data analysis and exploration.

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Exploring Twitter Trends Using the Search API

- **Objective :** Discover what topics are currently trending on Twitter by using its **search API** .

Example 1-3: Retrieving Twitter Search Trends

1. **Importing the Twitter Module :**

python Copy code `import twitter`

2. **Creating a Twitter Search Instance :**

- Instantiate the Twitter class by specifying the domain:

python Copy code `twitter_search = twitter.Twitter(domain= "search.twitter.com")`

3. **Fetching Trends :**

- Retrieve current trends:

python Copy code `trends = twitter_search.trends()`

4. **Listing Trending Topics :**

- Extract and display the names of trending topics:

python Copy code `[trend['name'] for trend in trends['trends']]`

- Example output might include:

- #ZodiacFacts
- #nowplaying
- Justin Bieber
- SNL

Understanding the Twitter Module

- **Usage Pattern :**

- Use the twitter module by creating an instance of the Twitter class and calling methods that correspond to specific API endpoints. For example:

python Copy code `twitter_search .trends()`

- This calls the URL: `http://search.twitter.com/trends.json` , which can also be accessed directly in a web browser.

- **Contextual Note :**

- The trends reflect real-time interests, such as `SNL` (Saturday Night Live), which appeared due to its airing on a Saturday night.

- **Bookmark the Twitter API Documentation :**

- It's advisable to keep the official Twitter API documentation handy for frequent reference.

Example 1-4: Paging Through Twitter Search Results

1. **Initializing a List for Search Results :**

python Copy code `search_results = []`

2. **Fetching Multiple Pages of Results :**

- Loop through to collect five pages of search results, each containing 100 tweets related to `SNL` :

python Copy code `for page in range (1 , 6): search_results.append(twitter_search .search(q= "SNL" , rpp= 100 , page=page))`

3. **Understanding REST Queries :**

- The equivalent REST query for the search would be:

arduino Copy code `http: //search.twitter.com/search.json?q=SNL&rpp=100&page=1`

- This clear mapping between the REST API and the python module simplifies writing code that interacts with Twitter.

4. **Result Storage :**

- The `search_results` list now contains five objects, each representing a batch of 100 results.

Example 1-5: Displaying Search Results

- To print the search results in a readable JSON format, you can use the built-in **json** package available in Python 2.6 and later.

This structured approach allows you to efficiently access and analyze trending topics and related tweets on

Example 1-5: Pretty-Printing Twitter Data as JSON

1. Importing the JSON Module :

python Copy code `import json`

2. Displaying Search Results :

- Use the `json.dumps()` function to format and print the search results in a readable JSON format:

python Copy code `print json.dumps(search_results, sort_keys = True, indent= 1)`

3. Output Structure :

- The output will show details about the search results, including:
 - **completed_in** : Time taken for the query.
 - **max_id** : Highest tweet ID in the results.
 - **next_page** : URL parameters for fetching the next page of results.
 - **page** : Current page number.
 - **query** : The search term used.
 - **refresh_url** : URL to refresh the search based on the latest tweets.
 - **results** : An array containing individual tweet data, which includes:
 - **created_at** : Timestamp of the tweet.
 - **from_user** : Username of the tweet author.
 - **from_user_id** : User ID (note this may not match the actual Twitter ID as of late 2010).
 - **geo** : Geographic data (if available).
 - **id** : Unique tweet ID.
 - **iso_language_code** : Language of the tweet.
 - **metadata** : Additional information about the tweet, such as its type.
 - **profile_image_url** : URL of the author's profile image.
 - **source** : Platform used to send the tweet.
 - **text** : Content of the tweet.
 - **to_user_id** : ID of the user mentioned (if any).

4. Important Note :

- As of late 2010, the **from_user_id** field may not correspond to the actual Twitter user ID. Check **Twitter API Issue #214** for more information. This is a minor issue for example code but is crucial to note for further development.

5. Next Steps :

- More details about processing and analyzing these results will be explored in later chapters. For now, focus on how tweets are organized under the **results** key in the response.

6. Extracting Tweet Text :

- In the following example, a method will be shown to extract text from the 500 tweets using a double list comprehension, highlighting a nested loop approach.

This proces

Example 1-6: A Simple List Comprehension in Python

1. List Comprehension Basics :

python Copy code `tweets = [r['text'] \ for result in search_results \ for r in result['results']]`

- This **list comprehension** creates a list of tweet texts from the `search_results` .

2. Understanding List Comprehensions :

- Although they can appear complex when written on one line, breaking them down into nested loops makes their purpose clearer.
- This comprehension is equivalent to: python Copy code `tweets = [] for result in search_results : for r in result['results']: tweets.append(r['text'])`
- List comprehensions provide better performance compared to traditional nested loops and offer a concise syntax once familiar.

3. Lexical Diversity :

- **Lexical diversity** measures the uniqueness of words in a text. It is calculated as:
$$\text{Lexical Diversity} = \frac{\text{Number of Unique Tokens}}{\text{Total Number of Tokens}}$$
 Lexical Diversity = Total Number of Tokens / Number of Unique Tokens

4. Calculating Lexical Diversity for Tweets :

- Example code for calculating lexical diversity:

python Copy code `words = [] for t in tweets: words += [w for w in t.split()] total_words = len(words) # Total number of words unique_words = len (set (words)) # Number of unique words lexical_diversity = 1.0 * unique_words / total_words # Lexical diversity avg words_per_tweet = 1.0 * sum ([len (t.split()) for t in tweets]) / len (tweets) # Average words per tweet`

5. Results :

- Total words: **7238**
- Unique words: **1636**
- Lexical diversity: **0.226**
- Average words per tweet: **14.48**

6. Interpreting Results :

- A lexical diversity of **0.23** indicates that about **one in four words** is unique.
- With an average of **14 words per tweet** , this means each tweet contains just over **3 unique words** .
- This suggests that each tweet carries around **20% unique information** .

7. Important Note :

- In Python versions before 3.0, the division operator can truncate results to integers. To avoid this, multiply by **1.0** to ensure floating-point division.

This analysis of tweets helps to understand the richness of language used, which can be valuable

Analyzing Tweets with Natural Language Toolkit (NLTK)

1. Purpose of Analysis :

- **Identify Abbreviations** : Users often shorten words to fit within Twitter's 140-character limit.
- **Frequency Distribution** : Understanding the most and least common terms used in tweets can provide insights into user behavior and trends.

2. Using NLTK :

- **Natural Language Toolkit (NLTK)** : A widely-used module for text analytics that offers various tools for tasks such as:
 - Calculating common metrics
 - Information extraction
 - **Natural Language Processing (NLP)**
- **Suitability** : While NLTK may not be the most advanced option available, it serves as a solid foundation for beginners in text processing.

3. Alternatives to NLTK :

- If NLTK's performance does not meet your needs, consider:
 - **Open Source Alternatives** : Search for and compare different tools.
 - **Custom Solutions** : Develop your own toolkit through research and prototyping.
 - **Commercial Products** : License professional-grade software, though this can be expensive and time-consuming.

4. Installation of NLTK :

- Install using `easy_install` : `bash Copy code $ easy_install nltk`
- **Restart Interpreter** : After installation, restart your Python interpreter to use NLTK.

5. Data Preservation :

- Use the `cPickle` module to save your data (pickle it) before exiting your session. Example code:
`python Copy code f = open ("myData.pickle" , "wb") import cPickle cPickle.dump(words, f)
f.close()`

6. Common Issues :

- If you encounter an **ImportError** related to YAML when importing NLTK, resolve it by installing `pyYaml` : `bash Copy code $ easy_install pyYaml`

7. Documentation and Resources :

- Visit the official NLTK website for detailed documentation, including the reference book "Natural Language Processing with Python" by Steven Bird, Ewan Klein, and Edward Loper.

By using NLTK, you can conduct comprehensive text analyses on T

Analyzing Current Twitter Conversations

1. Purpose of Analysis :

- **Understanding Current Topics** : One of the primary motivations for mining Twitter data is to identify what people are currently discussing.

2. Frequency Analysis :

- **Basic Technique** : Frequency analysis is a straightforward method for determining the most talked-about topics.
- **Use of NLTK** : The **Natural Language Toolkit (NLTK)** simplifies frequency analysis by providing an easy-to-use API.

3. Example of Frequency Analysis :

- Code Snippet:

```
python Copy code import nltk import cPickle words = cPickle.load( open ( "myData.pickle" )) freq
dist = nltk.FreqDist(words)
```

- **Most Frequent Tokens** : The top 50 most common words include terms like:
 - snl , on , rt , is , to , watch , justin , @justinbieber , etc.
- **Least Frequent Tokens** : The bottom 50 least common words include terms like:
 - what?! , whens , whoooo!!!! , wii , youtube?? , etc.

4. Key Observations :

- The frequent tokens provide **valuable information** related to people, events, and activities.
- In contrast, the infrequent tokens tend to represent **noise** that lacks meaningful insight.
- The presence of `snl` at the top of the list aligns with the search topic, while mentions of **Justin Bieber** suggest significant conversation around this individual.

5. Alternative Counting Methods :

- **Python's Collections.Counter** : Python 2.7 introduced the `Counter` class, which can also perform counting tasks. This can be a good alternat

Analyzing Twitter Conversations: Insights and Techniques

1. Key Tokens in Conversations :

- **Popular Tokens** : The analysis revealed frequent mentions of `@justinbieber` , `justin` , and `bieber` , indicating a significant interest in Justin Bieber.
- **SNL Connection** : The tokens `tina` and `fey` reference **Tina Fey** , highlighting her association with **Saturday Night Live (SNL)** . This context suggests that many people were excited about his appearance on the show.

2. Importance of Frequency Analysis :

- **Efficient Data Processing** : While a human could skim tweets to gather insights, doing this continuously for large datasets is impractical. Frequency analysis automates this process, allowing for real-time understanding of trending topics.
- **Powerful Yet Simple Tool** : Despite its simplicity, frequency analysis is an effective method for answering the question, "What are people talking about right now?"

3. Identifying Retweets :

- **RT Token** : The presence of `RT` indicates that many tweets were retweets, suggesting a high volume of duplicate or similar messages. For example:
 - A tweet might read: "RT @SocialWebMining Justin Bieber is on SNL 2nite. w00t?!"
- This token helps understand the spread of information and the dynamics of Twitter conversations.

4. Graph Representation of Social Data :

- **Using NetworkX** : To visualize relationships among Twitter users, we can use **NetworkX** to create a **directed graph (digraph)** . This graph will show how information flows between users, particularly those who retweet each other.
- **Challenges with Twitter API** : While Twitter APIs can analyze retweets, they require numerous API calls, which can quickly exhaust usage quotas. Thus, building a digraph using local data is more efficient.

5. Conclusion :

- Frequency analysis and graphing relationships provide essential insights into Twitter conversations, allowing for efficient tracking of trends and user interactions. This foundational understanding sets the stage for deeper analyses

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Twitter API Rate Limits and Retweet Extraction

1. API Rate Limits :

- **Authenticated Requests** : Limited to **350 calls per hour** .
- **Anonymous Requests** : Limited to **150 calls per hour** .
- For detailed information, visit the [Twitter Rate Limiting page](#) .
- **Future Chapters** : Chapters 4 and 5 will cover strategies to optimize API usage and creative data collection techniques.

2. Extracting Retweet Information :

- **Using Regular Expressions** : We can reliably identify retweets using simple regex patterns based on Twitter conventions:
 - **Patterns to Search** :
 - **RT** followed by a username (indicates a retweet).
 - **via** followed by a username (indicates source of information).
- **Username Format** : Twitter usernames start with @ and can include letters, numbers, and underscores.

3. Example of Regular Expression Usage :

- **Python Code** :

```
python Copy code import re
rt_patterns = re.compile ( r"(RT|via) ((?:\b\W*\w+)+)" , re.IGNORECASE)
example_tweets = [ "RT @SocialWebMining Justin Bieber is on SNL 2nite. w00t?!?" , "Justin Bieber is on SNL 2nite. w00t?!? (via @SocialWebMining)" ]
for t in example_tweets :
    rt_patterns.findall(t)
```
- **Output** :
 - `[('RT', ' @SocialWebMining')]`
 - `[('via', ' @SocialWebMining')]`
- The `findall` method returns tuples with matching text, which can be cleaned using `strip()` to remove leading spaces.

4. Regular Expressions Overview :

- **Basic Concept** : Regular expressions (regex) are a fundamental programming tool for pattern matching in text.
- **Learning Resources** : For more information, refer to the `re` module documentation and Friedl's *Mastering Regular Expressions* (O'Reilly) for in-depth knowledge.

This summary captures the essentials of API li

Building a Retweet Relationship Graph with NetworkX

1. Tweet Data Structure :

- The Twitter API provides a structured format that includes the **username** of the person tweeting and allows for the extraction of **retweet originators** .

2. Graph Representation :

- **Nodes** represent **usernames** .
- A **directed edge** between nodes indicates a **retweet relationship** .
- Each edge carries additional information: **tweet ID** and **tweet text** .

3. Example of Graph Construction :

- **Import Necessary Libraries :**

python Copy code `import networkx as nx import re`

- **Create a Directed Graph :**

python Copy code `g = nx.DiGraph()`

- **Flatten Tweet Data :**

- Combine multiple pages of tweets into a single list for easier processing:

python Copy code `all_tweets = [tweet for page in search_results for tweet in page["results"]]`

- **Function to Extract Retweet Sources :**

- Define a function using regex to find retweet sources:

python Copy code `def get_rt_sources (tweet): rt_patterns = re.compile (r"(RT|via) ((?:\b\W*\w+)+)" , re.IGNORECASE) return [source.strip() for tuple in rt_patterns.findall(tweet) for source in tuple if source not in ("RT" , "via")]`

- **Add Edges to the Graph :**

- Loop through all tweets and add edges based on retweet sources:

python Copy code `for tweet in all_tweets : rt_sources = get_rt_sources (tweet["text"]) if not rt_sources : continue for rt_source in rt_sources : g.add_edge (rt_source , tweet["from_user"], { "tweet_id" : tweet["id"]})`

4. Analyzing the Graph :

- **Number of Nodes :**

- `g.number_of_nodes ()` returns the total count of unique users in the graph.

- **Number of Edges :**

- `g.number_of_edges ()` shows how many retweet relationships exist.

- **View Edges with Data :**

- `g.edges(data=True)[0]` displays the first edge along with its data.

- **Connected Components :**

- Use `len(nx.connected_components (g.to_undirected ()))` to count distinct groups of connected nodes.

- **Node Degree :**

Analyzing Twitter Data with NetworkX

1. Context of Analysis :

- The analysis is based on a small subset of tweets related to **SNL** —only **500 tweets** out of potentially tens of thousands. This limited scope provides initial insights but may not represent the entire conversation.

2. Graph Characteristics :

- **Nodes and Edges :**
 - In the graph, there are **160 unique users (nodes)** and **125 retweet relationships (edges)** .
- **Average Degree :**
 - The average degree of a node is approximately **1.28** , indicating that on average, each user is connected to about **one other user** . This suggests that while some users retweet multiple times, many are only connected to one other user.
- **Connected Components :**
 - The graph has **37 subgraphs** , meaning it is **not fully connected** . This implies that there are groups of users who are not interacting with others outside their subgroup.

3. Degree Distribution Insights :

- The **degree** of a node indicates how many connections it has. In this case:
 - Most nodes have a degree of **1** , showing they are connected to only one other user.
 - A few nodes have degrees between **2 and 9** , indicating they connect to a small group of users.
 - There is one **outlier node** with a degree of **37** , which means this user is highly connected compared to others.

4. Distribution Pattern :

- The degree distribution closely follows a **Power Law** and features a **"heavy" or "long" tail** . This means that while most users have few connections, a small number have many connections.
- Understanding these distributions is important as they often appear in various data contexts.

5. Further Exploration :

- While this analysis provides a foundational understanding, there is encouragement to explore concepts like **Zipf's Law** , which relates to the distribution of words and other phenomena that exhibit similar patterns.

This analysis helps in understand

Introduction to Automatable Heuristics and Graph Visualization

1. Purpose of the Chapter :

- This chapter serves as an **introduction** to thinking creatively about data analysis using **automatable heuristics** . It aims to inspire readers to explore available data opportunities.

2. Visualizing Tweet Graphs :

- **Graphviz** is a key tool in the visualization field. It provides a method to visualize graphs created from tweet data by exporting them to the **DOT language**, a simple text format compatible with Graphviz.
- Installation of Graphviz is straightforward across all platforms, and users can download it from the official website.

3. Dependencies :

- For users on **Unix-based systems**, installing **PyGraphviz** through `easy_install` is typical to enable NetworkX to generate DOT output.
- **Windows users** might face challenges installing PyGraphviz, but it is relatively easy to adjust code to create DOT output without it.

4. Generating DOT Output :

- Example 1-12 shows how to generate DOT language output for graph visualization, regardless of the platform:
 - If PyGraphviz is installed, the graph can be exported directly.
 - If not, a simple workaround is provided to create the DOT format manually.

5. Sample DOT Output :

- The generated DOT output takes the form shown in Example 1-13. This output illustrates the relationships between nodes (users) and includes tweet IDs to provide context.

6. Issue with Windows Installation :

- A long-standing issue exists for Windows users regarding PyGraphviz installation, which requires C code compilation. This problem remains unresolved, but users can still produce DOT output through alternative methods.

By visualizing tweet data graphs, users can gain insights into the relationships and interactions within the data, reinforcing

Example DOT Language Output and Graph Visualization

1. DOT Language Example :

- Example 1-13 shows a **DOT language output** for retweet relationships among users:

```
strict digraph { " @ericastolte " -> " bonitasworld" [tweet_id = 11965974697 ]; " @mpcoelho " -> " Lil_Amaral " [tweet_id = 11965954427 ]; " @BieberBelle123 " -> " BELIEBE4EVER" [tweet_id = 11966261062 ]; " @BieberBelle123 " -> " sabrina9451" [tweet_id = 11966197327 ]; }
```
- This format describes a directed graph where each edge represents a retweet, with the associated tweet ID included.

2. Converting DOT to Image :

- The next step is to convert the DOT output into an image format. **Graphviz** provides various layout algorithms for visualizing graphs.
- The **circo** tool is recommended for rendering a **circular layout**, which is suitable for the expected "hub and spoke" topology of the data.
- On Unix-based systems, the following command converts the DOT file into a PNG image:

```
ruby Copy code $ circo - Tpng - Osnl search_results snl search_results .dot
```


- **Windows users** can use the **GVedit** application to achieve the same result.

3. Visual Confirmation :

- Viewing the generated graph confirms the earlier analysis, specifically highlighting **@justinbieber** as the most connected node, indicating his popularity during the SNL episode.

4. Potential for More Data :

- If more tweets had been analyzed, the graph likely would have shown additional interconnected subgraphs, offering deeper insights.

5. Further Exploration :

- While the chapter primarily aims to establish a development environment and introduce basic concepts, readers are encouraged to explore additional graph analysis.

6. Future Visualizations :

- Graphviz will be utilized in later chapters, and mastering it is recommended for aspiring data scientists. Other visualization methods will also be covered.

7. Interactive Visualization Script :

- The chapter concludes with a **turn-key example script** that synthesizes concepts from the chapter and adds visualization capabilities.
- This script allows users to input a search term, fetch data, and visualize it as an interactive HTML5 graph.
- The script is available at the official code repository: [GitHub - Retweet Visualization](<http://github.com>)

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Overview of Protovis and Graph Visualization

1. Introduction to Protovis :

- **Protovis** is a visualization toolkit that will be revisited in several chapters throughout the book. It allows for advanced data visualization techniques.

2. Example Output :

- **Figure 1-4** displays the output generated by Protovis from the example script. This demonstrates the capabilities of the toolkit.

3. Potential for Expansion :

- The sample script provided serves as a **starting point**, indicating that much more can be accomplished with Protovis beyond the initial example.

4. Graph Visualization with Graphviz :

- **Figure 1-2** shows the search results visualized using a **circular layout** with Graphviz, highlighting how data can be effectively represented graphically.

Summary

- The content emphasizes the utility of **Protovis** for visualizing data and suggests that the initial examples are merely foundational, with pote

Closing Remarks on Python Development for Twitter Data

1. Using GVedit :

- **GVedit** is recommended for **Windows users** as an alternative to the command prompt for interacting with Graphviz.

2. Chapter Overview :

- This chapter introduced you to using **Python's interactive interpreter** for exploring and visualizing **Twitter data**.

3. Comfort with Tools :

- It's crucial to feel **comfortable with your Python development environment** before proceeding. Spend time familiarizing yourself with:
 - **Twitter APIs** : Understand how to collect and manipulate data.
 - **Graphviz** : Learn how to visualize data effectively.

4. Further Exploration :

- Consider exploring **Canviz** , a project that renders Graphviz graphs in web browsers using the

element.

- Investigate **IPython** , which enhances the Python interpreter with features like:
 - **Tab completion**
 - **History tracking**

5. Future Work :

- Future chapters will focus more on **runnable scripts** , but being productive while experimenting and debugging in your environment is essential.

Summary

- The chapter emphasized the importance of becoming familiar with Python tools and libraries essential for data exploration and visualization

Interactive Protovis Graph Overview

1. Graph Type :

- The graph is a **force-directed layout**, which means it visually represents relationships in a way that mimics physical forces, helping to clarify connections between nodes.

2. Visualization Purpose :

- This graph specifically visualizes **retweet relationships** for the query related to “**JustinBieber.**”

3. Interactivity :

- The graph is **interactive**, allowing users to explore the data dynamically, enhancing understanding of how users are connected through retweets.

Summary

- The Protovis graph effectively illustrates the retweet network for **Justin Bieber**, showcasing connections in an engaging and understand

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Chapter 2: Microformats: Semantic Markup and Common Sense Collide

1. Introduction to Microformats :

- **Microformats** are conventions for embedding structured data into web pages, enhancing their functionality.
- They allow for the inclusion of “**smarter data**” easily by content authors, making web pages more informative.

2. Purpose and Relevance :

- Microformats help organize data in a **value-added** way, providing clarity and structure.
- As web development evolves, the use of microformats is on the rise, with nearly **50% of web developers** adopting them.

3. Key Microformats Covered :

- The chapter focuses on several specific microformats:
 - **XFN (XHTML Friends Network)** : Used for marking up relationships between people.
 - **geo** : For embedding geographical coordinates.
 - **hRecipe** : To describe recipes.
 - **hReview** : For structuring reviews of items, such as recipes.

4. Practical Applications :

- Examples in this chapter include:
 - **Mining relationships** from blogrolls using XFN.

- **Extracting geographical coordinates** from web pages.
- **Parsing recipes** from websites like Food Network.
- **Analyzing reviews** of recipes.

5. Future of Microformats :

- At the time of writing, microformats were integral to **Rich Snippets** in Google search results, suggesting a strong future presence.
- Google aims for at least **50% of web pages** to use semantic markup, promoting broader adoption of microformats.

6. Conclusion :

- Microformats may not always be classified as “social data,” but their role in **social data mashups** is expected to grow.
- The chapter sets the stage for understanding and utilizing microformats effect

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Microformats and Decentralized Social Networks

1. Role of Microformats :

- Microformats could act as a **catalyst** for creating robust decentralized social networks, contrasting with centralized platforms like **Facebook** .

2. Semantic Web Technologies :

- Technologies like **FOAF (Friend of a Friend)** haven't yet reached widespread adoption, which is expected given the Web's history of gradual, evolutionary change rather than rapid revolutions.
- The evolution of microformats is a key example of improving the Web by bridging existing technologies with emerging standards.

3. Importance of Microformats :

- Microformats allow for the **embedding of structured data** related to social networking, calendars, resumes, and bookmarks directly within HTML.
- They maintain **backward compatibility** , making them accessible and easy to implement.

4. Diversity and Adoption :

- The ecosystem of microformats is diverse; some like **geo** are well-established, while others are gaining popularity among search engines and social media platforms.
- Recent developments include Google supporting **hRecipe** as part of their Rich Snippets initiative.

5. Summary of Popular Microformats :

- The following table highlights some notable microformats and their purposes:

Technology	Purpose	Popularity	Markup Specification	Type
XFN	Representing human-readable relationships in links	Widely used, especially in blogging	Semantic HTML, XHTML	Microformat
geo	Embedding geocoordinates for people and objects	Widely used, e.g., MapQuest, Wikipedia	Semantic HTML, XHTML	Microformat
hCard	Identifying people and contact information	Widely used	Semantic HTML, XHTML	Microformat
hCalendar	Embedding iCalendar data	Gaining traction	Semantic HTML, XHTML	Microformat

Technology	Purpose	Popularity	Markup Specification	Type
hResume	Embedding resume and CV information	Widely used by sites like LinkedIn	Semantic HTML, XHTML	Microformat

6. Conclusion :

- Microformats provide a structured way to embed data that enhances the Web, and their growing presence indicates a shift toward more **semantic and machine-read

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Overview of Various Data Embedding Technologies

1. hRecipe :

- **Purpose** : Identifies recipes on web pages.
- **Popularity** : Widely used by niche sites like **foodnetwork.com** .
- **Markup Specification** : Semantic HTML, XHTML.
- **Type** : Microformat.

2. Microdata :

- **Purpose** : Embeds name/value pairs into HTML5 web pages.
- **Popularity** : An emerging technology gaining traction.
- **Markup Specification** : HTML5.
- **Type** : W3C initiative.

3. RDFa (Resource Description Framework in attributes) :

- **Purpose** : Embeds clear facts into XHTML pages using specialized vocabularies.
- **Popularity** : Variable success; some vocabularies like **FOAF** are gaining ground while others remain obscure.
- **Markup Specification** : XHTML.
- **Type** : W3C initiative.

4. Open Graph Protocol :

- **Purpose** : Embeds profiles of real-world entities in XHTML pages.
- **Popularity** : Gaining traction, especially due to the influence of the **Facebook** platform.
- **Markup Specification** : XHTML (RDFa-based).
- **Type** : Facebook platform initiative.

5. Trends in Microformats :

- The success of a microformat often correlates with support from major players like **Google** , **Yahoo!** , and **Facebook** . More backing leads to higher chances of widespread adoption and usefulness for data mining.

Semantic Markup Explained

1. Difference Between Semantic HTML and XHTML :

- **Semantic HTML** : Focuses on the meaning of content through tags that emphasize the information rather than its presentation. Original HTML did not effectively promote this.
- **XHTML** : A well-formed XML standard developed to separate content from presentation. It allows content to

be authored in XML without presentation concerns, which can then be transformed into XHTML for rendering in browsers.

- **Key Characteristics of XHTML :**
 - Nearly identical to HTML but maintains XML validity.
 - Requires elements to be closed or self-closing, properly nested, and written in lowercase.

This distinction highlights the evolution t

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Overview of XHTML and Its Adoption Challenges

1. XHTML Benefits :

- **Well-Formed Content :** XHTML allows content to be validated against an XML schema, offering advantages such as:
 - Custom attributes using **namespaces** .
 - Compatibility with **semantic web technologies** like **RDFa** .

2. Lack of Adoption :

- Despite its benefits, XHTML did not gain widespread acceptance. Possible reasons include:
 - Issues with **Internet Explorer** .
 - Confusion among developers about the correct **MIME types** for browsers.
 - Inadequate **XML developer tools** .
 - The impracticality of the entire web needing to convert to XHTML at once.
- As a result, **HTML 4.01** continues to dominate, leaving XHTML and its technologies like RDFa on the fringes.

3. Hopes for HTML5 :

- The web development community is optimistic that **HTML5** will create a long-awaited convergence of standards.

Practical Applications of XFN

1. Introduction to XFN :

- **XFN (XHTML Friends Network)** is a microformat used to identify relationships among people via keywords in the `rel` attribute of anchor tags.
- Commonly found in blogs and blogroll plugins, such as those in **WordPress** .

2. Example of XFN Markup :

- An example of XFN in action is illustrated below:

html Copy code < div > < a href = "http://example.org/matthew" rel = "me" > Matthew < a href = "http://example.com/users/jc" rel = "friend met" > J.C. < a href = "http://example.com/users/abe" rel = "friend met co-worker" > Abe < a href = "http://example.net/~baseeret" rel = "spouse met" > Baseeret < a href = "http://example.net/~lindsaybelle" rel = "child met" > Lindsay Belle

3. Understanding Relationships :

- From the `rel` attributes, you can easily interpret relationships:

- **Matthew** is identified as a person who knows various individuals: friends, a spouse, and a child.
- Relationships like “friend met” and “spouse met” indicate real-life connections rather than solely online associations.

4. Power of XFN :

- XFN's strength lies in its simplicity and the structured nature of the information it provides.
- It becomes especially powerful when used broadly, allowing for a clearer understanding of social connections, assuming the data remains current.

Overall, XFN exemplifies how microformats can effectively convey social relationships through

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Understanding XFN's Limitations and Opportunities

1. XFN as a Relationship Indicator :

- **XFN (XHTML Friends Network)** effectively shows how people are connected through specific **keywords** in the `rel` attribute of hyperlinks.
- While it provides a clear connection (e.g., “Matthew and Baseeret are married with a child named Lindsay Belle”), it doesn't offer deep insights or additional context about those relationships.

2. Need for Additional Sources :

- To gain more understanding beyond basic connections, you must rely on other information sources and techniques.

3. Harvesting XFN Data :

- A simple script can be created to harvest XFN data, similar to services like **rubhub** , a social search engine that indexes XFN information from various websites.

Mining XFN Data with Web Scraping

1. Web Scraping Overview :

- Mining XFN data involves web scraping, which can be straightforward, especially with the help of the **BeautifulSoup** library.

2. Example Script :

- Below is a sample script for scraping XFN content from a webpage. It uses **Ajaxian** , a popular blog, as a source.

```
python Copy code # -*- coding: utf-8 -*- import sys import urllib2 import HTMLParser from BeautifulSoup import BeautifulSoup # Use the URL provided as a command line argument URL = sys.argv[ 1 ] XFN_TAGS = set ( [ 'colleague' , 'sweetheart' , 'parent' , 'co-resident' , 'co-worker' , 'muse' , 'neighbor' , 'sibling' , 'kin' , 'child' , 'date' , 'spouse' , 'me' , 'acquaintance' , 'met' , 'crush' , # ... additional tags can be added here ] )
```

3. Installation Requirement :

- Ensure you have the **BeautifulSoup** package installed by using `easy_install BeautifulSoup` before running the script.

Conclusion

Using XFN microformats allows for simple representation of social connections on the web. While it doesn't provide extensi

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Web Scraping XFN Data: Detailed Breakdown

1. Scraping Process :

- The script uses **urllib2** to fetch a webpage using a provided URL. If it fails, it prints an error message.
- It employs **BeautifulSoup** to parse the fetched page. If parsing fails, an error is reported.

2. Extracting Links :

- The script searches for all `anchor ()` tags on the page.
- It checks if the `rel` attribute exists and if it contains any keywords from the **XFN TAGS** set (like 'friend', 'contact').
- If a match is found, it prints the name, URL, and relationship tags of each person.

```
python Copy code # Example snippet for reference anchorTags = soup.findAll( 'a' ) for a in anchorTags: if a.has_key ( 'rel' ): if len ( set ( a[ 'rel' ].split() ) & XFN_TAGS ) > 0 : tags = a[ 'rel' ].split() print a.contents[ 0 ], a[ 'href' ], tags
```

3. BeautifulSoup Version Note :

- In version **3.1.x**, BeautifulSoup switched to using **HTMLParser** instead of **SGMLParser**, leading to some complaints about robustness.
- The author recommends either reverting to version **3.0.x** for better performance or catching parsing errors as shown.

4. Sample Output :

- When run against a URL containing XFN data, the script outputs each friend's name, their blog URL, and the type of relationship. For example:

```
python Copy code Dion Almaer http://www.almaer.com/blog/ [ u'me' ] Ben Galbraith http://weblogs.java.net/blog/javaben/ [ u'co-worker' ]
```

5. Building a Social Graph :

- If the friends' URLs contain XFN data or useful information, you can follow these links to expand your social graph.
- The next steps in the process would follow a **breadth-first search** approach to systematically gather more data.

Pseudocode for Breadth-First Search

1. Initialization :

- Create an **empty graph** to hold the relationships.
- Create an **empty queue** to track which nodes (friends) need processing.

This systematic approach helps in creating a comprehensive representation of social connections through XFN data, enhancing understanding of relationships in

Building a Social Graph Using Breadth-First Search

1. Graph Initialization :

- Start by **adding the root node** (initial user) to the graph.
- Add this root node to a **queue** for processing.

2. Processing Loop :

- Repeat the following steps until a maximum depth is reached or the queue is empty:
 - **Remove a node** from the queue.
 - For each **neighbor** of that node:
 - Check if the neighbor has not been processed yet.
 - If not processed, **add it to the queue** and the graph.
 - Create an **edge** in the graph connecting the current node to its neighbor.

3. Benefits of This Approach :

- This method automatically creates **bidirectional edges** between nodes, making it easy to identify **mutual friends** without extra tracking. This is particularly useful in social networking scenarios.

4. Example Code :

- Example 2-4 demonstrates using breadth-first search to crawl XFN links: python Copy code # -*- coding: utf-8 -*- import sys import urllib2 from BeautifulSoup import BeautifulSoup import networkx as nx ROOT URL = sys.argv[1] MAX DEPTH = int (sys.argv[2]) if len (sys.argv) > 2 else 1

5. Depth and Graph Size :

- Running the code with a maximum depth of two can generate a **large graph** , especially in active communities. You can visualize the graph or run metrics on it to analyze connections.

6. Additional Notes for Windows Users :

- Windows users should refer to “**Visualizing Tweet Graphs** ” on page 14 to understand the necessary workaround for using `nx.drawing.write_dot` .

By following this breadth-first search strategy, you can efficiently map out social connections and visualize re

Building a Directed Graph for Social Connections

1. Setup :

- Define a set of **XFN relationship tags** to categorize connections:
 - 'co-worker' , 'muse' , 'neighbor' , 'sibling' , 'kin' ,
 - 'child' , 'date' , 'spouse' , 'me' , 'acquaintance' ,
 - 'met' , 'crush' , 'contact' , 'friend' .

2. Graph Initialization :

- Create an **output file** named `graph.dot` .
- Initialize `depth` to 0 and create a directed graph object `g` using **NetworkX** .
- Start with a **queue** containing the root URL (`ROOT_URL`).

3. Breadth-First Search :

- Loop through the graph until the defined **maximum depth** is reached:
 - Increment the **depth** counter.
 - Swap `queue` and `next_queue` to process the next level of URLs.

4. Fetching and Parsing Pages :

- For each URL in the queue:
 - Attempt to **open the URL** using `urllib2` . If it fails, print an error message and continue to the next URL.
 - Parse the page content using **BeautifulSoup** . If parsing fails, print an error message and continue.

5. Adding Nodes and Edges :

- Check if the node (URL) already exists in the graph; if not, add it.
- For each anchor tag () found:
 - Check if it has a `rel` attribute containing any of the defined XFN tags.
 - If a matching tag is found:
 - Extract the friend's URL and add an **edge** from the current node to this friend's URL in the graph.
 - Label the edge with the relationship type from the `rel` attribute.
 - Also, label the friend node with the anchor's text.

Summary

This approach builds a directed graph of social connections by scraping and parsing web pages for XFN data, using a breadth-first search strategy to explore relationships while ensuring all relevant connections are documented within the graph structure.

Completing the Social Graph and Saving Output

1. Adding Friends to the Queue :

- For each valid friend's URL (`friend_url`), append it to `next_queue` to explore in subsequent iterations.

2. Directory Management :

2. Directory management :

- Check if an output directory named **'out'** exists. If not, create it to store the graph output files.

3. Saving the Graph :

- Attempt to write the graph `g` to a **DOT file** using NetworkX's `write_dot` method.
- If an `ImportError` occurs (e.g., due to missing Graphviz tools), a workaround is used for Windows users:
 - Construct a **DOT representation** manually:
 - For each edge in the graph, create labels for both nodes and edges.
 - Write the constructed DOT data to a file named `graph.dot` in the 'out' directory.

4. Generating Graph Visualizations :

- For users on **Unix-like systems** : Use the command `circo -Tpng -Ograph graph.dot` in the terminal to generate a visual representation of the graph.
- For **Windows users** : Use `circo.exe` with similar options or utilize the **GVedit** desktop application for visualization.

5. Importance of Labels :

- The `label` attribute for nodes and edges is essential. It ensures that when the graph is rendered using Graphviz, the relationships and identities are clearly defined and visually represented.

Summary

This process efficiently constructs a social graph based on XFN relationships, manages output directories, saves the graph in DOT format, and provides methods for visu

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Analysis of the XFN Data Graph

1. Graph Overview :

- The **directed graph (digraph)** illustrates relationships among eight individuals, centered around **Dion Almaer** .
- The edge label “ **Me** ” signifies that Dion owns the blog <http://ajaxian.com> .

2. Relationship Insights :

- The graph shows various connections but does not clarify the depth of relationships.
- For instance, while Dion is connected to both **Ben Galbraith** (co-worker) and other individuals (friends), it's unclear if he shares a stronger bond with Ben.
- To explore this, one could crawl Ben's XFN data to uncover additional **co-worker** tags and better understand their professional connections. For more on this topic, refer to **Chapter 6** .

Brief Analysis of Breadth-First Techniques

1. Understanding Algorithm Evaluation :

- It's crucial to evaluate algorithms based on two primary criteria:
 - **Efficiency** : How well the algorithm performs in terms of speed and resource usage.
 - **Effectiveness** : The quality of the results produced.

2. Performance Metrics :

- Standard performance analysis examines:
 - **Worst-case time complexity** : How long it takes to run the algorithm under the least favorable conditions.
 - **Space complexity** : The amount of memory required for execution, especially with large data sets.

3. Algorithm Type :

- The breadth-first approach used in this example is essentially a **breadth-first search (BFS)** , which systematically explores the nodes layer by layer

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Understanding Breadth-First Search (BFS) in Graph Expansion

1. Breadth-First Search (BFS) Basics :

- In this context, we are expanding the graph without specific **search criteria** ; our goal is simply to grow the graph to a maximum depth or until there are no more nodes to explore.
- A typical **breadth-first search** would have specific goals, but here we focus on crawling links indefinitely.

2. Bounded Breadth-First Search :

- A more practical version of BFS is the **bounded breadth-first search** , which sets a limit on how deep the search goes—just like in our example.

3. Complexity Analysis :

- The **time and space complexity** of a breadth-first search can be expressed as $O(b^d)$, where:
 - **b** = branching factor (average number of neighbors per node)
 - **d** = depth of the search
- For instance, if each node has five neighbors and you search to a depth of two, you could end up with 31 total nodes:
 - 1 root + 5 neighbors + 25 neighbors from the first five nodes.

4. Branching Factor Calculations :

- Table 2-2 illustrates how the number of nodes increases with varying **branching factors** and depths:
 - **Example** :
 - For a branching factor of 2 and depth of 5, total nodes = 63.

5. Practical Considerations :

- In real-world applications, the performance of the algorithm is often **I/O bound** , meaning it spends much of its time waiting for data from network requests (like `urlopen`).
- Using techniques like **threading** can help improve performance by managing multiple requests simultaneously.

6. Quality of Results :

- A simple visual inspection of the resulting graph can confirm connections between people, indicating successful data collection.
- However, variations in URLs can lead to `**du`

Managing URL Variations and Geographic Data in Social Connections

1. URL Variations and Identity Consolidation :

- Different URLs referencing the same person (e.g., `http://example.com/~matthew` vs. `http://www.example.com/~matthew`) can lead to duplicate nodes in a graph.
- **XFN** addresses this with the `rel="me"` attribute, which helps consolidate identities across various links.
- **Google's Social Graph API** uses this method to connect a user's multiple profiles across different platforms.

2. Trailing Slash Issues :

- URLs may differ by the presence or absence of a trailing slash. While many websites redirect automatically to resolve this, it can still be a minor issue.
- **SocialGraph Node Mapper** is an open-source project that standardizes URLs, addressing variations like trailing slashes and the "www" prefix, ensuring different URLs that point to the same person are recognized as one.

3. Importance of Geocoordinates :

- **Geocoordinates** can link disparate data sets, making them relevant in social contexts.
- Data tied to specific locations can provide insights into social connections and behaviors. For example, understanding a person's location may reveal their interests, such as cooking preferences based on local ingredients.

4. Using Geo Microformats :

- The **geo** microformat embeds location data in web pages, inspired by vCard properties.
- This format can cluster people and information based on geographic context, facilitating social connections.

5. Example of Geo Microformats :

- The geo microformat allows for two methods of embedding location information. An example snippet demonstrates how to describe a place, like Franklin, Tennessee, using this microformat.

Conclusion

Understanding and managing URL variations through XFN and employing geocoordinates with microformats are essential for building a cohesive social graph. This approach enhances identity recognition and reveals connections

Geo Microformats: Markup and Extraction

1. Geo Microformat Example :

- **HTML Markup :**
 - **Multiple Class Approach :** html Copy code `< span style = "display: none" class = "geo" > < span class = "latitude" > 36.166 < span class = "longitude" > -86.784`
 - **Single Class Approach** (using semicolon as separator): html Copy code `< span style = "display: none" class = "geo" > 36.166; -86.784`
- This markup wraps **latitude** and **longitude** values in tags with the class **geo** , providing a structured way to present geographic data.

2. Usage of Geo Microformats :

- Many popular sites, including **Wikipedia** , **Yahoo! Local** , and **MapQuest Local** , utilize the **geo** microformat to expose structured location data.

3. Hiding Geo Data :

- To keep geo information hidden from users while still accessible for machines, developers often use CSS:
 - **style="display: none"** : Completely removes the element from the layout.
 - **style="visibility: hidden"** : Hides the element but retains its space on the page.

4. Extracting Geo Data :

- **Example Program :**
 - The following Python script demonstrates how to parse geo microformat data from a MapQuest Local page: python Copy code

```
# -*- coding: utf-8 -*- import sys import urllib2 from BeautifulSoup import BeautifulSoup import HTMLParser # Pass in a URL such as http://local.mapquest.com/franklin-tn url = sys.argv[ 1 ] try : page = urllib2.urlopen(url) except urllib2.URLError, e: print 'Failed to fetch ' + url raise e exit() try : soup = BeautifulSoup(page) except HTMLParser.HTMLParseError: print 'Failed to parse ' + url
```
- This script fetches the content of a specified URL and prepares to extract geo data using **BeautifulSoup** .

Conclusion

Geo microformats provide a structured method for embedding geographic coordinates in web pages. They enable the extraction of valuable location data while often keeping this information hidden from users, allowing for efficient d

Parsing Geo Data from Microformats

1. Extracting Geo Information :

- After fetching the webpage content, the script looks for the **geo** tag: python Copy code `geoTag = soup.find(True , 'geo')`
- **Data Retrieval :**
 - If multiple elements are found:
 - **Latitude** and **Longitude** are extracted from their respective tags:
python Copy code `lat = geoTag.find(True , 'latitude').string lon = geoTag.find(True , 'longitude').string print 'Location is at' , lat, lon`
 - If only one element is found:
 - The string containing both coordinates is split:

```
python Copy code (lat, lon) = geoTag.string.split( ';' )
```

- **Whitespace** is trimmed from both values.

- If no geo tag is found:

- The script outputs:

```
python Copy code print 'No location found'
```

2. Significance of Microformats :

- Microformats provide **structured data** that enhances readability for both humans and machines.
- While a person may easily interpret location information from a webpage, machines require clear tagging to understand the same context.
- This embedding of **semantics** reduces ambiguity, making data easier to process for crawlers and developers, fostering innovation for all parties involved.

3. Visualizing Geo Data :

- Once geo data is extracted, the next step is to visualize it.
- **Microform.at** is a helpful tool that extracts various microformats from a webpage, allowing users to visualize data easily.
- For instance, using the **Wikipedia article** on U.S. National Parks, one can quickly load and visualize embedded geo data interactively.

Conclusion

Extracting and utilizing geo data through microformats allows for better data organization and accessibility. This structured approach benefits both human users and automated systems, enabling clearer communication and innovative applications. Tools like microform.at fu

Visualizing Geo Data with KML

1. Microform.at Results :

- Microform.at can extract **geo data** from web pages, such as the Wikipedia article "List of National Parks of the United States."
- This service provides the extracted data in various formats, including **KML** (Keyhole Markup Language).

2. Using KML for Visualization :

- KML is a simple and effective way to visualize geo data.
- Users have two main options to view KML data:
 - **Download** the KML file to use with **Google Earth** .
 - **Directly input** a URL containing KML data into the **Google Maps** search bar for instant access.

3. Interactivity and Ease of Use :

- In Microform.at, clicking on the "KML" link will prompt a **file download** .
- Alternatively, users can right-click to **copy** the KML URL to their clipboard and paste it into Google Maps for viewing.
- This integration simplifies the process of visualizing geo data without needing extensive technical skills.

4. Example Visualization :

- An example URL for KML results can be constructed like this:

perl Copy code `http://microform.at/?type=geo&url=http%3A%2F%2Fen.wikipedia.org%2Fwiki%2FList_of_U.S._national_parks`

- This URL leads to the visualization of geo data on Google Maps for the specified Wikipedia article.

Conclusion

Using tools like Microform.at to extract and visualize geo data via KML makes accessing geographical information straightforward and user-friendly. This approach enhances the understanding of spatial relations

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Google Maps and National Parks

Overview: Google Maps can display all national parks in the United States using KML (Keyhole Markup Language) results from microform.at.

Key Concepts:

- **Semantic Markup:** Starting with a **Wikipedia article** that contains semantic markup (like **geo data**) allows for easy visualization. This makes data analysis efficient and insightful with minimal effort.
- **Browser Extensions:** Tools like the **Firefox Operator add-on** further simplify this process, enhancing user experience.
- **Practical Application:** A practical activity is to combine national park data with **contact information** from your **LinkedIn** network. This could help plan enjoyable activities during business trips.
- **Data Analysis Technique:** Refer to “**Geographically Clustering Your Network**” (page 193) for methods on analyzing geo data using **k-means clustering** to find clusters and centroids.

This process demonstrates how to leverage data effectively for both personal and professional purposes while keeping it straightforward.

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Slicing and Dicing Recipes for Health

Overview: Google's Rich Snippets initiative has increased the use of microformats , particularly hRecipe and hReview , on popular food websites. This enables better visibility of recipes and reviews.

Key Concepts:

- **Microformats Awareness:** The rise of microformats allows for structured data presentation, improving user experience and search engine indexing.
- **Online Dating Application:** Imagine a **dating service** that matches people for dinner dates based on:
 - **Proximity:** How close individuals live to each other.
 - **Food Preferences:** Types of cuisines they enjoy, such as vegetarian or BBQ.
- **Success Factors:** Pairing individuals with similar dining preferences (e.g., vegetarians vs. BBQ lovers) can enhance the likelihood of a successful date. Additional factors like allergens and organic ingredient preferences can further refine matches.
- **Food Network Example:** The **Food Network** utilizes microformats effectively by exposing:
 - **hRecipe** for recipe information.
 - **hReview** for recipe reviews.
- **Data Parsing:** This section illustrates how to extract and analyze structured data from recipe and review pages, although no permanent data storage or free text analysis is conducted here. Future chapters will cover:
 - **CouchDB** for data storage and sharing (Chapter 3).
 - **Natural Language Processing (NLP)** for understanding content (Chapter 7).
- **Example Code:** An adaptation (Example 2-7) is provided for parsing **hRecipe** data, specifically for a **Pad Thai** recipe.

This approach showcases the potential of combining culinary interests with technology for innovative applications.

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Parsing a Recipe Using hRecipe Microformat

Overview: This script extracts key information from a recipe webpage using the hRecipe microformat. The example URL is for a Pad Thai recipe from the Food Network.

Key Components:

1. URL Input:

- The script accepts a URL as a command-line argument (e.g., `http://www.foodnetwork.com/recipes/alton-brown/pad-thai-recipe/index.html`).

2. Function Definition: `parse_hrecipe(url)`

- **Purpose:** Fetch and parse the recipe data.

3. Error Handling:

- **URL Fetching:** Uses `urllib2.urlopen()` to fetch the page.
 - If unsuccessful, it prints an error message.
- **HTML Parsing:** Uses **BeautifulSoup** to parse the HTML content.
 - Handles parsing errors appropriately.

4. Data Extraction:

- **Finding hRecipe:** Searches for the `hrecipe` class in the parsed HTML.
- **Recipe Information:**
 - **Name:** Extracted from the `fn` tag.
 - **Author:** Found in the `author` tag.
 - **Ingredients:** Compiles a list from all `ingredient` tags.
 - **Instructions:** Gathers instructions from the `instructions` tag, ensuring to handle different types of HTML elements correctly.

5. Return Value:

- Returns a dictionary containing:
 - **name:** Recipe name
 - **author:** Author of the recipe
 - **ingredients:** List of ingredients
 - **instructions:** List of instructions

6. Output:

- The final recipe data is printed in a JSON format with indentation for readability.

This script demonstrates a straightforward approach to extracting structured data from web pages, highlighting the utility of microformats in web scraping and recipe management.

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Parsed Results for Pad Thai Recipe

Overview: When parsing Alton Brown's Pad Thai recipe, the output includes key details such as instructions, ingredients, the recipe name, and the author.

Parsed Data Structure:

json Copy code

```
{ "name": "Pad Thai", "author": "Recipe courtesy Alton Brown, 2005", "ingredients": [ "1-ounce tamarind paste", "3/4 cup boiling water", "2 tablespoons fish sauce", "2 tablespoons palm sugar", "1 tablespoon rice wine vinegar", "4 ounces rice stick noodles", "6 ounces Marinated Tofu, recipe follows", "1 to 2 tablespoons peanut oil", "1 cup chopped scallions, divided", "2 teaspoons minced garlic", "2 whole eggs, beaten", "2 teaspoons salted cabbage", "1 tablespoon dried shrimp", "3 ounces bean sprouts, divided", "1/2 cup roasted salted peanuts, chopped, divided", "Freshly ground dried red chile peppers, to taste", "1 lime, cut into wedges" ], "instructions": [ "Place the tamarind paste in the boiling water and set aside ...", "Combine the fish sauce, palm sugar, and rice wine vinegar in ...", "Place the rice stick noodles in a mixing bowl and cover with ...", "Press the tamarind paste through a fine mesh strainer and add ...", "Place a wok over high heat. Once hot, add 1 tablespoon of the ...", "If necessary, add some more peanut oil"
```

to the pan and heat until ..."]}

Key Points:

- **Recipe Details:** The parsed data includes:
 - **Name:** "Pad Thai"
 - **Author:** Alton Brown
 - **Ingredients:** A comprehensive list including tamarind paste, fish sauce, and various other components.
 - **Instructions:** Step-by-step cooking directions.
- **Analysis Opportunity:** While not a social analysis, examining variations of the same recipe could reveal correlations between certain ingredients and recipe ratings or reviews. For instance, analyzing different **Pad Thai** recipes could highlight which ingredients are common and which are less frequent.

Collecting Restaurant Reviews:

- **Introduction to hReview:** This section introduces the **hReview** microformat, commonly used by services like **Yelp** to expose restaurant ratings.
- **Example Code:** Example 2-9 illustrates how to extract hReview data from Yelp, using a sample URL for a notable Thai restaurant.

This provides a foundation for understanding how microformats like hRecipe and hReview facilitate data extraction and analysis in culinary and restaurant contexts.

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Parsing hReview Data from Yelp

Overview: The implementation of hReview can vary significantly across platforms. This example demonstrates how to parse review data from Yelp, noting that Yelp does not follow the hCard standard for reviewers.

Key Components:

1. **Script Setup:**
 - **URL Input:** The script accepts a URL containing **hReview** data, such as `http://www.yelp.com/biz/bangkok-golden-fort-washington-2` .
2. **Function Definition:** `parse_hreviews (url)`
 - **Purpose:** Extract pertinent information from a Yelp review page.
3. **Error Handling:**

- **Fetching Page:** Uses `urllib2.urlopen()` to access the page, with error handling for URL fetch failures.
- **Parsing HTML:** Utilizes **BeautifulSoup** to parse the HTML content, with error handling for parsing issues.

4. Data Extraction:

- **Finding hReview Instances:** Searches for all elements with the `hreview` class.
- **Review Information Extraction:** For each review, it extracts:
 - **Reviewer:** Retrieved from the `reviewer` tag. (Note: Not implemented as an **hCard** in Yelp's structure.)
 - **Review Date:** Extracted from the `dtreviewed` tag.
 - **Rating:** Obtained from the `rating` tag, specifically the `value-title` attribute.
 - **Description:** Text from the `description` tag.
 - **Item Reviewed:** Text from the `item` tag.

5. Notes on Variability:

- The quality and structure of **hReview** implementations can vary widely, which means results may differ across sites.
- This script does not serve as a strict **hReview** spec parser, emphasizing the need for flexibility.

This example illustrates the challenges and considerations when working with microformats, particularly in the context of varying implementations like Yelp's hReview.

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Collecting and Analyzing hReview Data

Overview: The script collects hReview data from Yelp, organizing it into a structured format for further analysis.

Key Components:

1. Data Structure Creation:

- Each review is stored in a dictionary containing:
 - **Reviewer:** The name of the reviewer.
 - **Review Date:** The date the review was made.
 - **Rating:** The rating given by the reviewer.
 - **Description:** The text of the review.

```
python Copy code all hreviews .append({ 'reviewer' : reviewer, 'dtreviewed' : dtreviewed,
'rating' : rating, 'description' : description, })
```

2. Return Value:

- The function returns a list of all collected reviews.

3. Example Output:

- A truncated sample of the output might look like this:

```
json Copy code [ { "reviewer" : "Nick L." , "description" : "Probably the best Thai food in the
metro area..." , "dtreviewed" : "4/27/2009" , "rating" : "5" } , ... ]
```

4. Limitations:

- Current implementations by Yelp and others do not provide sufficient data to meaningfully connect reviewers.
- Future improvements in data linking could enhance possibilities for social interactions based on reviews.

5. Potential Analyses:

- Plotting the **average rating** of a restaurant over time to track performance.
- Analyzing the text within review descriptions for insights.

6. Data Handling:

- The process of formatting JSON data for spreadsheets is not detailed here, but a downloadable spreadsheet is suggested for ease of use.

7. Innovation in Food Data:

- The intersection of technology and food data opens up numerous possibilities for innovation, as highlighted by the book **Cooking for Geeks**.
- As food websites enhance their APIs, new opportunities for creative applications will emerge.

This section emphasizes how to effectively collect and analyze review data, while also pointing to the exciting potential for future developments in the field.

Summary of Microformats

Key Takeaways:

- **Definition of Microformats:**

Microformats are a method of enhancing HTML markup to display structured information clearly, such as **recipes**, **contact information**, and **human relationships**.

- **Potential Benefits:**

They enable existing content to become more explicit and compliant with predictable standards, enhancing data accessibility and usability.

- **Future Growth:**

Expect increased interest and development in microformats, especially as **HTML5** and its **microdata** features gain popularity.

- **Further Exploration:**

If you have extra time, explore **Google's Social Graph API**. Note that this is distinct from **Facebook's Open Graph**, which uses **RDFa** and is discussed in Chapter 9, along with related protocols like **XFN** and **FOAF**.

This chapter emphasizes the significance of microformats in improving data structure and the exciting developments on the horizon as web technologies evolve.

Chapter 3: Mailboxes: Oldies but Goodies

Overview: This chapter focuses on analyzing email data, which remains a vital source of information despite the rise of social media. It explores various questions about email interactions and discusses the advantages of using email data for analysis.

Key Questions Explored:

1. Mail Volume:

- Who sends out the most emails?

2. Response Timing:

- Is there a specific time of day or day of the week that yields the best response rates?

3. Interaction Analysis:

- Which individuals exchange the most messages?

4. Discussion Topics:

- What subjects generate the most active discussions?

Advantages of Email Data:

- **Decentralization:**

Email data is scattered across the web, making it more accessible than centrally managed social media data, which is subject to strict service provider rules.

- **Data Collection Methods:**

Users can collect their own email data by subscribing to mailing lists or requesting archives from list owners.

- **Enterprise Control:**

Organizations typically have full control over their email data, enabling them to conduct aggregate analyses and identify trends.

Data Set for Analysis:

- **Enron Data Set:**

The chapter utilizes the public **Enron data set**, which offers realistic examples for analyzing email interactions, providing a valuable resource for illustration.

Conclusion: Despite the popularity of social networking, email remains a significant data source with unique advantages for analysis, particularly in understanding communication patterns and trends.

mbox: Overview of Unix Mailboxes

Definition: An mbox file is a simple text file format used for storing concatenated email messages. It's designed to be easily accessible with text-based tools.

Structure of mbox Files:

1. Message Separator:

Each email message starts with a **From_ line**, formatted as:

sql Copy code `From user@example.com Fri Dec 25 00 : 06 : 42 2009`

This line includes:

- The sender's email address
- A timestamp in a fixed-width format (asctime)

2. Message Boundary:

Messages in an mbox file are separated by a **From_ line** that follows exactly two new lines (except for the first message).

Example of mbox File: A sample mbox slice may look like this:

scss Copy code

```
From santa@northpole.example.org Fri Dec 25 00 : 06 : 42 2009 Message-ID : <16159836.1075855377439@mail.northpole.example.org> References : <88364590.8837464573838@mail.northpole.example.org> In-Reply-To : <194756537.0293874783209@mail.northpole.example.org> Date : Fri, 25 Dec 2001 00 : 06 : 42 - 0000 (GMT) From : St. Nick To : rudolph@northpole.example.org Subject : RE : FWD : Tonight Mime-Version : 1.0 Content-Type : text/plain; charset=us-ascii Content-Transfer-Encoding: 7 bit Sounds good. See you at the usual location. Thanks, -S
-----Original Message----- From: Rudolph Sent: Friday, December 25 , 2009 12 : 04 AM To: Claus, Santa Subject: FWD: Tonight Santa - Running a bit late. Will come grab you shortly. Standby. Rudy Begin forwarded message: >
Last batch of toys was just loaded onto sleigh.
```

Exporting Options: Most email clients offer an "export" or "save as" feature to convert email data into the mbox format, making it widely compatible across different systems.

Conclusion: The mbox format is a crucial standard for email storage in Unix systems, known for its simplicity and ease of use with text-processing tools.

Example Analysis of an mbox File

Message Overview: The example features two messages from an mbox file, with a focus on a message from Buddy the Elf .

Details of Buddy's Message:

- **Sender:** Buddy the Elf
 - **Email:** buddy.the.elf@northpole.example.org
 - **Title:** Chief Elf, Workshop Operations
- **Recipient:** workshop@northpole.example.org
- **Date:** Fri, 25 Dec 2001 00:03:34 GMT
- **Subject:** Tonight

Message Content:

- **Main Point:** Notification that the last batch of toys has been loaded onto the sleigh.
- **Closing:** "Please proceed per the norm. Regards, Buddy."

Message Structure:

- **Message-ID:** Unique identifier for the message: <88364590.8837464573838@mail.northpole.example.org> .
- **Headers:**
 - **References:** Points to other messages in the conversation.
 - **In-Reply-To:** Indicates which message this one is responding to.

Context of the Messages:

- The first message from Buddy serves as a notification.
- The second message is a reply from Santa to Rudolph, which references Buddy's message.
- An intermediary message from Rudolph to Santa, which forwards Buddy's notification, is implied but not shown.

Threading Messages:

- **Importance of Headers:** The **Message-ID** , **References** , and **In-Reply-To** headers help organize messages into a threaded discussion. This allows for algorithms to effectively display conversation threads, making it easier to follow discussions.

Conclusion: The structure of mbox files, along with the use of headers, provides a comprehensive way to analyze email communications and understand the flow of discussions within a mailbox.

Understanding Email Message Parsing

Focus on Parsing Tools:

- We will utilize **Python modules** to simplify email parsing.
- No detailed discussion on complex topics like **multipart content** , **MIME** , or **7-bit content transfer encoding** is included, but there are plenty of resources available for those interested in these areas.

Importance of Email Headers:

- **Headers** are crucial for understanding email flow.
- In our example, ambiguity arises from how different email clients handle quoted content:
 - **Rudolph's email client** uses > characters to quote forwarded content.
 - **Santa's reply** omits quoting, presenting a plain text response.

Challenges in Email Parsing:

- Analyzing the conversation's flow can be challenging due to these inconsistencies.
- Many email clients offer an option to view **extended headers** , which provide more context than the standard headers.

Example and Illustration:

- **Example 3-2** depicts the message flow discussed.
- **Figure 3-1** shows how extended headers are displayed in **Apple Mail** , emphasizing the importance of these headers in understanding the full context of email communications.

Message Flow Analysis

Example 3-2: Timeline of Email Messages

1. **Buddy sends a message** to the workshop on **December 25, 2001** at 00:03:34 GMT.
2. **Rudolph forwards** Buddy's message to Santa, adding his own note on **December 25, 2009** at 12:04 AM.
3. **Santa replies** to Rudolph on **December 25, 2001** at 00:06:42 GMT.

Utilizing Mail Clients and mbox Format

- **Efficiency** : You can do a lot with email data without needing to fully recreate a mail client.
- **Import/Export Options** : Check if your mail client supports **importing/exporting** in the **mbox format** . This allows you to analyze your mailbox using tools discussed in this chapter.

Parsing mbox Data with Python

Example 3-3: Converting mbox to JSON

- This example provides a simple way to convert mbox data into a more user-friendly **JSON structure** .

Key Functions :

- **decode('utf-8', 'ignore') :**
 - This function helps handle issues related to **UnicodeDecodeError** when working with text data.
 - You can specify how to deal with decoding errors:
 - **'strict'** raises an exception (default).
 - **'ignore'** skips problematic characters.
 - **'replace'** substitutes them with a placeholder.

Example Code Overview

python Copy code

```
# -*- coding: utf-8 -*- import sys import mailbox import email import quopri from BeautifulSoup import BeautifulSoup
try : import jsonlib2 as json # Faster than Python 2.6's standard library except ImportError: import json MBOX =
sys.argv[ 1 ] def cleanContent ( msg ): # Decode message from "quoted printable" format msg =
quopri.decodestring(msg) # Strip out HTML tags, if present
```

- This code snippet demonstrates how to read and clean email messages, mak

JSON Conversion of Email Messages

Code Breakdown

1. Parsing Message Content :

- The `soup = BeautifulSoup(msg)` creates a BeautifulSoup object from the email message.
- `return ''.join(soup.findAll(text=True))` extracts all the text content, stripping away HTML tags.

2. Function: `jsonifyMessage(msg)` :

- **Purpose** : Converts an email message into a JSON format for easier handling and analysis.
- **Initial Setup** : Creates a dictionary `json_msg` with an empty list for message parts.

3. Decoding Message Fields :

- For each key-value pair in the message:
 - Decodes values using `utf-8` while ignoring errors.
- Handles **To** , **Cc** , and **Bcc** fields:
 - If these fields exist, it cleans them by removing newlines, tabs, and spaces, and splits them into lists.

4. Processing Message Parts :

- Iterates over each part of the message using `msg.walk()` :
 - Skips multipart messages.
 - Collects content type and payload, decoding it to UTF-8.
 - Cleans the content using the `cleanContent` function.
 - Appends the structured content to `json_msg['parts']` .

5. Error Handling :

- Wraps processing in a try-except block to catch and report any errors encountered during parsing.

6. Reading mbox Files :

- Opens the mbox file in binary mode: `mbox = mailbox.UnixMailbox(open(MBOX, 'rb'), email.message_from_file)` .
- Iterates through messages until there are none left, converting each message into JSON format.

7. Output :

- Prints the final JSON structure, formatted for readability with `indent=4` .

Performance Notes

- As of Python 2.6.x, third-party libraries like **jsonlib2** offer significant speed improvements over the standard library's JSON module.
- Python 2.7 includes updates that make its standard JSON module competitive with third-party options, especially for larger JSON structures (over 100 MB), where performance differences can be substantial

Overview of the Email Parsing Script

Purpose : This script effectively extracts key information from email messages and converts it into a portable JSON object format.

Key Features

- **Basic Parsing** : Focuses on extracting important email components, creating a structured format that's easy to handle.
- **Quoted-Printable Decoding** : Utilizes the **quopri module** to decode quoted-printable text, which is a method for transmitting 8-bit data over a 7-bit communication channel.
- **HTML Tag Stripping** : Removes HTML tags to ensure that the content is clean and plain text is retained.

Sample JSON Output

The script generates a JSON output that includes vital email details. Below is a simplified structure of the output based on Example 3-4:

json Copy code

```
[{"From": "St. Nick ", "Content-Transfer-Encoding": "7bit", "To": [ "rudolph@northpole.example.org" ], "parts": [ {
  "content": "Sounds good. See you at the usual location.\n\nThanks,...", "contentType": "text/plain" } ], "References":
"<88364590.8837464573838@mail.northpole.example.org>", "Mime-Version": "1.0", "In-Reply-To": "
<194756537.0293874783209@mail.northpole.example.org>", "Date": "Fri, 25 Dec 2001 00:06:42 -0000 (GMT)",
"Message-ID": "<16159836.1075855377439@mail.northpole.example.org>", "Content-Type": "text/plain;
charset=us-ascii", "Subject": "RE: FWD: Tonight" }, { "From": "Buddy ", "Content-Transfer-Encoding": "7bit", "To":
[ "workshop@northpole.example.org" ], "parts": [ { "content": "Last batch of toys was just loaded onto sleigh.\n\n...",
"contentType": "text/plain" } ], "Mime-Version": "1.0", "Date": "Fri, 25 Dec 2001 00:03:34 -0000 (GMT)", "Message-
ID": "<88364590.8837464573838@mail.northpole.example.org>", "Content-Type": "text/plain; charset=us-ascii",
"Subject": "Tonight" } ]
```

Conclusion

This script serves as a practical tool for parsing email data into a structured format that can be easily analyzed or manipulated. It addresses common challenges in email parsing, such as decoding and content cleaning, making it a valuable resource for working with email data. For more in-depth information about quoted-printable encoding, see Wikipedia or refer to RFC 2045 .

Introduction

With your new ability to parse mail data into an accessible format, you can start analyzing it. This chapter focuses on the publicly available Enron mail data , which comes in the form of mbox files.

Enron Mail Data Files

- **Enron Data Downloads :**
 - **enron.mbox.gz** : Contains raw messages from “inbox” folders of the Enron dataset in mbox format.
 - **enron.mbox.json.gz** : This is the same data converted into JSON format using a previously discussed script.
- **Conversion Script :**
 - You can also download the script used to convert the Enron inbox data into mbox format at [GitHub](#).
- **Alternate Format :**
 - The official Enron data can be found at Carnegie Mellon University , but it is in a nonstandard format that includes additional information like calendaring details.

Using CouchDB for Email Analysis

- **CouchDB Overview :**
 - A **document-oriented database** ideal for working with JSON data. It provides **map/reduce capabilities** that help in creating indexes and performing analyses.
- **Advantages of Using CouchDB :**
 - Allows for a more **relaxed approach** to data analysis by avoiding the repetitive task of schema creation and modification.
 - You can easily analyze how many messages were sent by a specific individual or on a particular date.
- **Goal :**
 - By importing mbox data into CouchDB, you can efficiently conduct **aggregate frequency analysis** and address specific analytical questions related to the email data.

Conclusion

This section aims to show how to leverage CouchDB for analyzing mbox data in a straightforward manner, even for those unfamiliar with CouchDB's features. Using the right tools enhances the

REST-Based Interface

- **CouchDB's Advantage** : It offers a **REST-based interface** , making it easy to integrate with any web architecture. This allows seamless interaction with the database over HTTP.

Replication Capabilities

- **Easy Replication** : CouchDB provides simple replication features, enabling others to clone your databases and analyses effortlessly.

Understanding RESTful Web Services

- **Definition of REST** : REST (REpresentational State Transfer) is an architectural style introduced by Roy Fielding in his PhD dissertation. Key concepts include:
 - **Stateless Communication** : Clients and servers communicate without maintaining session information.
 - **Resource URIs** : Each resource is identified by a URI and can be manipulated using standard HTTP verbs:
 - **GET** : Retrieve a resource.
 - **PUT** : Create or update a resource.
 - **POST** : Append data to a resource.
 - **DELETE** : Remove a resource.
- **Example Usage** :
 - A URL like `http://example.com/blog` describes a "blog" resource.
 - **GET** on `/blog` retrieves the blog.
 - **PUT** on `/blog/foo` creates a new blog for user "foo".
 - **DELETE** on `/blog/foo` removes the blog.
 - **POST** on `/blog/foo` adds a new blog post.
- **Further Reading** : For more in-depth understanding, "RESTful Web Services" by O'Reilly is recommended for practical examples and advanced scenarios.

Getting Started with CouchDB

- **Installation** : Ensure you have CouchDB installed on your system. You can find binaries or compile from source.
- **Resources** :
 - **CouchOne** : Offers binaries and free CouchDB hosting options.
 - **Cloudant** : Another hosting option for CouchDB.

Viewing Documents in CouchDB

- Think of CouchDB as a **key-value store** , where:
 - **Keys** are arbitrary identifiers.
 - **Values** are JSON documents.
- **Futon Interface** : Access CouchDB's web-based admin interface (Futon) at `http://localhost:5984/` utils to manage documents and collections.

By leveraging CouchDB and understanding RESTful principles, you can effectively analyze document-based data like emails with ease and flexibility.

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Setting Up CouchDB and Python Client

Installing CouchDB

- **Installation** : After installing CouchDB, you'll need to perform additional administrative tasks to get everything ready.

Installing the Python Client

- **Python Client Module** : Install the CouchDB Python client using:
 - Command: `easy_install couchdb`
- **Documentation** : For more information, refer to the documentation available through **pydoc** or online at [CouchDB Python Package](#).

Next Steps

- With both CouchDB and the Python client installed, you can now begin coding to **ingest** the JSON-formatted mbox data into CouchDB.

This setup allows you to efficiently manage and analyze your email data using CouchDB's fea

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Exploring CouchDB with Futon

- **Futon Interface** : If you're new to CouchDB, spend a few minutes experimenting with the **Futon** web interface.
- **Further Learning** : If you prefer structured learning, consider reading the early chapters of **CouchDB: The Definitive Guide** , available online at [CouchDB Guide](#) .

Bulk Loading Documents into CouchDB

- **Loading Data** : Running the script from **Example 3-3** on the **enron.mbox** file creates a large JSON output (approximately 200 MB).
- **Script for Loading** : Example 3-5 shows how to load this data directly into CouchDB using the **couchdb-python** client. This approach is simpler than setting up a relational schema.

Performance Considerations

- **Loading Time** : Expect the script to take a few minutes on typical consumer hardware (like a laptop).
 - For reference, loading over 40,000 JSON objects results in more than **300 document transactions per second** , which is efficient.
- **Resource Monitoring** : You can monitor CPU usage (one core may be heavily used) using tools like **top** on Linux or **Task Manager** on Windows.

Development Tips

- **Start Small** : During development, work with a smaller subset of documents (e.g., a dozen JSONified Enron messages) for testing purposes.

CouchDB Performance Insights

- **Erlang and Concurrency** : While **Erlang** (CouchDB's underlying language) is known for handling high concurrency, CouchDB write operations are **append-only** and serialized, which means they are limited to one core per database for writing.
- **Batch Writes** : You can enhance performance by performing batch writes across multiple databases simultaneously, utilizing more CPU cores effectively.

Example 3-5: Loading JSON Data into CouchDB

- **Script Purpose** : This script loads JSON data from a file (e.g., **enron.mbox.json**) into CouchDB.

Key Components of the Script

- **Imports** :
 - Uses **couchdb** for database operations.
 - Tries to import **jsonlib2** for JSON handling; defaults to Python's built-in **json** if unavailable.
- **File and Database Setup** :
 - Takes the JSON file name as a command-line argument.
 - Derives the database name from the file name (removing the extension).
 - Connects to a CouchDB server running locally at `http://localhost:5984` .
- **Database Creation** :
 - Creates a new database with the derived name.
- **Document Loading** :
 - Reads the JSON file and loads the documents into the newly created database in one operation (using `db.update`).

After Loading: Exploring Data

- **Browsing with Futon** : After loading the data, you can use **Futon** (CouchDB's web interface) to explore the documents. This may lead to questions about communication patterns among users.

Understanding Map/Reduce

- **Map/Reduce Overview** :
 - **Mapping Functions** : Create key/value pairs for each document in the database.
 - **Reduction Functions** : Aggregate these key/value pairs to derive insights (e.g., sum or average).
 - Example: To sum squares of numbers, a mapping function would square each number, while the reducer would calculate the total sum.
- **Applicability** : Map/reduce is effective for problems that can be broken down into parallel tasks but may not suit all scenarios.

Document Sorting in CouchDB

- **Sorting Behavior** :
 - Documents in CouchDB are sorted by their `id` value, which is auto-generated.
 - As a result, the sort order may not provide meaningful insight without additional organization or custom keys.

Conclusion

- This section prepares you to utilize CouchDB's map/reduce functionality to analyze communication data and provides a foundation for understanding document handling within the database.

Setting Up CouchDB for Date-Based Analysis

Why Sort by Date?

- **Purpose of Sorting** : To perform **efficient range queries** and conduct **time-series analysis** , sorting by **date** is beneficial.

Configuration for Python Map/Reduce Functions

- **CouchDB and Erlang** : CouchDB is built in **Erlang** , known for **high concurrency** and **fault tolerance** .
- **Default Query Language** : The standard way to write map/reduce functions is in **JavaScript** , but you can also use **Python** .
- **Benefits of Using Python** :
 - Easier syntax checking and highlighting.
 - Avoids the complexity of embedding JavaScript within Python code.

Steps to Configure CouchDB for Python

1. Modify Configuration File :

- Add a line to the `local.ini` configuration file to specify Python as the view server: `css Copy code [query servers] python = /path/ to /couchpy`
- Replace `/path/to/couchpy` with the actual path to your `couchpy` executable.
- Remember to **restart CouchDB** after making this change.

2. Finding `couchpy` Executable :

- On Unix systems, use the command: `bash Copy code which couchpy`
- For Windows, `easy install` will typically place `couchpy.exe` in `C:\PythonXY\Scripts` .

Handling Date Formats

- **Use of `dateutil`** : To manage the variability of date formats from emails, install the **`dateutil`** package: `Copy code easy install dateutil`
- This package simplifies the parsing and standardization of different date formats.

Example: Mapping by Date

- **Next Steps** : After configuring your CouchDB to use Python and installing `dateutil` , you can run scripts that map documents based on their date/time stamps. This allows you to analyze email data effectively.

Conclusion

- By configuring CouchDB to use Python for map/reduce functions and incorporating tools like `dateutil` , you can efficiently analyze date-related data in your email corpus. This setup enables smoother and more insi

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Mapping Documents by Date/Time in CouchDB

Overview

This example demonstrates how to create a simple Python mapper that organizes CouchDB documents based on their date/time stamps .

Key Components of the Script

1. Imports :

- Essential libraries include **couchdb** for database interaction and **dateutil** for date parsing.
- The **jsonlib2** library is attempted for JSON handling, defaulting to the built-in **json** if not available.

2. Database and Date Parameters :

- The script takes command-line arguments for the **database name** , **start date** , and **end date** in the `YYYY-MM-DD` format.

3. Connecting to CouchDB :

- A connection to the CouchDB server is established using: python Copy code `server = couchdb.Server('http://localhost:5984')` `db = server[DB]`

4. Date Mapping Function :

- The function `dateTimeToDocMapper(doc)` :
 - Checks if the document has a **Date** field.
 - Parses the date and converts it into a list of components (year, month, day, hour, minute, second).
 - Uses **yield** to create a key-value pair for mapping.

5. View Definition :

- A **ViewDefinition** is created to index the documents: python Copy code `view = ViewDefinition('index', 'by_date_time', dateTimeToDocMapper, language='python')` `view.sync(db)`
- This establishes a mapping view that can be queried later.

6. Querying the Database :

- The script constructs the **start** and **end** keys for the date range.
- It queries the database for documents within the specified date range using: `python Copy code for row in db.view('index/by date_time ', startkey=start, endkey=end): docs.append(db.get(row. id))`

7. Output :

- The resulting documents are printed in a formatted JSON structure for easy reading.

Conclusion

This script effectively maps and retrieves documents from CouchDB based on their date/time stamps, facilitating organized data analysis. By using Python for the mapping process, it simplifies the handling of date formats and allows for powerful querying capabilities.

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Understanding the Code: Date/Time Mapping Function

Key Function: `dateTimeToDocMapper`

- **Purpose** : This custom generator function takes a document as input and emits it, keyed by a **convenient date value** . This makes it easier to manipulate and sort the documents.
- **Side-Effect-Free** : The mapping function does not alter the original document passed to it, adhering to CouchDB's principle that mapping functions must not have side effects.
- **View Definition** : In CouchDB terminology, `dateTimeToDocMapper` creates a view named “**by date_time** ”, which is part of a design document called “**index.**” You can verify this in CouchDB's Futon interface by selecting "Design documents."

Performance Insights

- **Initial Run** : The first time you execute the mapping function, it may take around **five minutes** to complete, utilizing one CPU core heavily.
 - **Indexing Time** : Approximately **80%** of this duration is spent building the index.
- **Subsequent Queries** : After the index is established, subsequent queries are much faster, typically around **20 seconds** to retrieve about **2,200 documents** (roughly **110 documents per second**).

Index Verification

- You can confirm that all documents are indexed by date by checking the “**by date_time** ” index in the Futon interface. This indexing is crucial for further analysis tasks, such as counting documents that meet specific criteria.

Map/Reduce-Inspired Frequency Analysis

Importance of Frequency Analysis

- **Exploratory Task** : Frequency analysis is a foundational step when examining a new dataset, as it provides valuable insights with minimal effort.

Frequency by Date/Time Range

- While the **by date_time index** sorts documents by date/time, it doesn't facilitate counting the frequencies of documents by common time periods (like year, month, or week).
- Instead of writing complex client-side code to calculate frequencies from the index, it is more efficient to let **CouchDB** handle this task. This requires a simple adjustment to the existing mapping approach.

Summary

- The `dateTimeToDocMapper` function is essential for indexing documents by date, enabling efficient retrieval and analysis.
- Establishing an index initially may take time, but it greatly enhances the performance of subsequent queries.
- Frequency analysis is vital for data exploration, and leveraging CouchDB's capabilities simplifies this process significantly.

Mapping and Reducing Functions for Frequency Analysis

Overview

To enhance the analysis of documents in CouchDB, we can use a mapping function combined with a reducing function . This approach allows us to efficiently count occurrences of documents by date/time.

Mapping Function

- **Purpose** : The mapping function will emit a value of **1** for each date/time stamp in the documents.
- **Output** : Each emitted value represents a single occurrence, creating a key for every date/time entry.

Reducing Function

- **Functionality** : The reducing function will count how many times each key (date/time stamp) appears.
- **Outcome** : This allows us to obtain a total count of documents for each specific date/time.

Example Code

Refer to Example 3-7 for the implementation of this mapping and reducing approach.

Additional Requirements

- **Installation** : Before running the example, you need to install the **prettytable** package using `easy_install` . This package helps in generating visually appealing tabular output for displaying results.

Conclusion

By using a simple mapping function to emit values and a reducing function to count those values, we can effectively analyze the frequency of documents by date/time in CouchDB. This method streamlines data analysis and enhances the understanding of communication patterns.

Understanding Map/Reduce in CouchDB

Key Concepts

- **Reducing Functions** : These functions operate only on values that correspond to the same key. This means they summarize or count data based on specific criteria, such as date/time.

Resources for Learning

- While a complete introduction to **map/reduce** is not covered here, you can find helpful resources online, including:
 - The **CouchDB wiki** .
 - An **interactive JavaScript tool** for practical understanding.

Important Note on rereduce

- The **rereduce parameter** is significant in certain situations, though it is not needed in the examples in this chapter. It's mentioned to remind you of its importance in more complex scenarios.

Example Code: Counting Messages by Date

Example 3-7 illustrates how to implement a mapper and reducer to count the number of messages by date using Python.

Code Structure

- The code uses the **PrettyTable** library to format the output neatly, making it easier to read and analyze the results.

By using map/reduce effectively, you can perform powerful analyses on your data, such as counting messages sent on different dates.

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Implementing Map/Reduce with CouchDB

Key Components

- **Server Connection :**

```
python Copy code server = couchdb.Server( 'http://localhost:5984' ) db = server[DB]
```

This code connects to the CouchDB server running on localhost.

- **Mapper Function :**

```
python Copy code def dateTimeCountMapper ( doc ): from dateutil.parser import parse from datetime
```

```
import datetime as dt if doc.get( 'Date' ): date = list (dt.timetuple(parse(doc[ 'Date' ]))[:-3 ]) yield ( date , 1 )
```

- This function extracts the date from each document and yields a key-value pair, where the key is the date and the value is 1 .

- **Reducer Function :**

```
python Copy code def summingReducer ( keys, values, rereduce ): return sum (values)
```

- This function sums the values passed to it, effectively counting the documents with matching keys.

View Definition

- **Creating a View :** python Copy code

```
view = ViewDefinition( 'index' , 'doc count_by_date_time ' ,
dateTimeCountMapper, reduce_fun =summingReducer, language= 'python' ) view.sync(db)
```

 - A view called **doc count_by_date_time** is defined, combining the mapper and reducer functions.

Output Formatting

- **Using PrettyTable for Output :** python Copy code

```
fields = [ 'Date' , 'Count' ] pt =
PrettyTable(fields=fields) [pt.set field_align (f, 'l' ) for f in fields] for row in db.view(
'index/doc count_by_date_time ' , group_level = 3 ): pt.add_row ([ '-' .join([ str (i) for
i in row.key]), row.value]) pt.printt()
```

 - This code formats the output into a readable table, grouping message counts by year, month, and day.

Debugging Tips

- If you need to debug your Python mappers or reducers, printing to the console may not work. Instead, you can append debug information to a file: python Copy code

```
open ( 'debug.log' , 'a' )
```

Summary

- The **doc count_by_date_time** view utilizes a mapper to emit date keys and a reducer to sum the counts of documents with matching keys. The **rereduce** parameter facilitates incremental reduction without requiring special handling in this context. This allows for efficient aggregation of document counts over specified time periods.

Rereducing Concept

- **Rereducing** : This process is relevant when multiple reduce operations are necessary, particularly when aggregating results from previous reductions. For more details, refer to “A Note on rereduce” on page 128 or find resources online.

Group Level Parameter

- **Purpose** : The **group level** parameter allows you to perform frequency analyses at different date/time granularities.
- **Functionality** :
 - CouchDB uses this parameter to slice the first N components of the date/time key, enabling automatic reduce operations on matching key/value pairs.
 - For example:
 - **First Component** : Tallies emails sent by **year** .
 - **First Two Components** : Tallies emails sent by **month** .
- **Querying** : Instead of querying for emails sent at an exact second, adjusting the **group level** allows for more meaningful aggregations.

Implementation

- When using the `db.view` function, you can control which part of the key is passed to the reducer using the **group level** argument.
- After computing the indexes, you can explore the resulting data in **Futon** to see the effects of different group levels.

Execution Time

- The execution time of the **dateTimeCountMapper** during the creation of the index for the **doc count_by_date_time** view is comparable to previous mapping functions, but it enables various useful queries based on the **group level** parameter.

Alternative Strategies

- While the **group level** parameter is effective for common time boundaries (year, month, week), you can also consider alternative strategies, such as using **milliseconds since the epoch** for different querying needs. In such cases, you would emit the milliseconds as the key.

Summary

The **group level** parameter in CouchDB is essential for controlling the granularity of frequency analyses, allowing you to efficiently summarize data by various time intervals. Un

Time-Based Analysis in CouchDB

Grouping and Filtering

- To perform **time-based analysis** independent of days (e.g., counting documents sent per hour), you cannot directly group by arbitrary items in a key (like Python slicing).
- Instead, you should create a new key with a suitable prefix, such as **[hour, minute, second]**.
- **Client-side filtering** would require iterating through the entire document collection, lacking the efficiency of pre-constructed indexes.

B-Trees Overview

- **B-Trees** are the primary data structure used in CouchDB and many other databases.
- **Key Characteristics** :
 - **Logarithmic performance** : Efficient for operations like inserts, updates, and deletes, even under challenging conditions.
 - **Balanced and sorted** : This structure maintains a sorted order, ensuring efficient data lookups with minimal disk reads.
- **Performance Advantage** : Since disk seeks (especially on traditional hard drives) are quick, B-Trees allow for rapid access to large volumes of data.
- **Origin** : The term "B-Tree" is commonly thought to be named after **Bayer**, who contributed to their invention. Learning about B-Trees is beneficial for understanding CouchDB's design and performance.

Frequency Analysis by Sender/Recipient

- Analyzing **email communication metrics** —like how many messages a person authored or interactions between groups—is crucial.
- **Example Implementation** : A mapper function can be created to count the number of communications between two individuals by examining the **To** and **From** fields of each message.
- **Extending Analysis** : You can include **Cc** and **Bcc** fields for a more comprehensive understanding, and this mapping function can easily be modified to compute various aggregate statistics.

Summary

CouchDB enables sophisticated time-based analysis by allowing custom keys for grouping, while its use of B-Trees ensures efficient data handling and querying. Additionally, frequency analysis based on sender/recipient interactions provides valuable insights into communication patterns.

Example 3-8: Counting Emails by Sender and Recipient

Code Overview

- **Purpose** : This code counts the number of emails sent from one person to multiple recipients.
- **Key Components** :
 - **Libraries Used** :
 - `couchdb` for database interaction.
 - `prettytable` for formatted table output.

Code Breakdown

1. Imports and Initialization :

```
python Copy code import sys import couchdb from couchdb.design import ViewDefinition from
prettytable import PrettyTable DB = sys.argv[ 1 ] # Database name from command line server =
couchdb.Server( 'http://localhost:5984' ) db = server[DB]
```

2. Mapper Function :

```
python Copy code def senderRecipientCountMapper ( doc ): if doc.get( 'From' ) and doc.get( 'To' ):
for recipient in doc[ 'To' ]: yield ([doc[ 'From' ], recipient], 1 )
```

- **Functionality** : Checks if both **From** and **To** fields exist. For each recipient in the **To** field, it yields a key-value pair where the key is a list containing the sender and recipient, and the value is 1.

3. Reducer Function :

```
python Copy code def summingReducer ( keys, values, rereduce ): return sum (values)
```

- **Functionality** : Sums the values associated with the same key, effectively counting the total messages between sender and recipient pairs.

4. View Definition :

```
python Copy code view = ViewDefinition( 'index' , 'doc count_by_sender_recipient ' ,
senderRecipientCountMapper, reduce_fun =summingReducer, language= 'python' ) view.sync(db)
```

5. Output Formatting :

```
python Copy code fields = [ 'Sender' , 'Recipient' , 'Count' ] pt = PrettyTable(fields=fields)
[pt.set field_align (f, 'l' ) for f in fields] for row in db.view( 'index/doc
count_by_sender_recipient ' , group= True ): pt.add_row ([row.key[ 0 ], row.key[ 1 ],
row.value]) pt.printt()
```

- **Functionality** : Sets up a table to display the results. It iterates through the view, adding rows for each sender-recipient pair and their respective counts.

Sorting Documents by Value

- **Sorting by Key vs. Value** : CouchDB sorts documents by key by default, which is useful but may not meet all needs.
- **Need for Value Sorting** : For example, when analyzing results to see the "top N" counts (like the most frequent sender-recipient pairs), sorting by value becomes essential.
- **Client-Side Sorting** : For smaller datasets, a client-side sort (e.g., using the quicksort algorithm) can be performed. Quicksort generally achieves an average case of $n \cdot \log(n)$ comparisons, which is efficient.

Summary

This example demonstrates how to count emails by sender and recipient using CouchDB, employing mapping and reducing functions for efficient data processing. Additionally, it highlights the importance of sorting by value in certain analyses, suggesting that for small datasets

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Sorting Documents by Key Using a Transpose Mapper

Overview

When dealing with larger datasets, traditional sorting methods in CouchDB may become inefficient. An effective alternative is to transpose reduced documents and load them into a separate database. This method allows for automatic sorting by key and can leverage multiple cores for performance improvements.

Example 3-9: Implementation

Code Breakdown

1. Imports and Initialization :

```
python Copy code import sys
import couchdb
from couchdb.design import ViewDefinition
from prettytable import PrettyTable
DB = sys.argv[ 1 ] # Name of the database from command line
server = couchdb.Server( 'http://localhost:5984' )
db = server[DB]
```

2. Querying Documents :

```
python Copy code docs = db.view( 'index/doc_count_by_date_time', group_level = 3 )
```

- This line queries documents grouped by **year, month, and day** from the existing database.

3. Creating a New Database :

```
python Copy code db_scratch = server.create(DB + '-num-per-day')
db_scratch.update(docs)
```

- A new database is created (e.g., DB-num-per-day) to store the queried documents.

4. Transpose Mapper Function :

python Copy code

```
def transposeMapper ( doc ): yield (doc[ 'value' ], doc[ 'key' ])
```

- This mapper transposes the documents, yielding a pair where the **value** (e.g., count of messages) is the key and the **key** (date) is the value.

5. View Definition :

python Copy code

```
view = ViewDefinition( 'index' , 'num_per_day ' , transposeMapper, language='python' ) view.sync(db_scratch )
```

- A new view is defined in the db_scratch database using the transpose mapper.

6. Output Formatting :

python Copy code

```
fields = [ 'Date' , 'Count' ] pt = PrettyTable(fields=fields) [pt.set_field_align(f, 'l' ) for f in fields] for row in db_scratch.view( 'index/num_per_day ' ): if row.key > 10 : # Only display counts greater than 10 pt.add_row ([ '-' .join([ str (i) for i in row.value]), row.key])
```

- A formatted table is created to display dates and counts, filtering for entries where the count exceeds 10.

Key Takeaways

- **Transpose Mapping** : This method allows you to sort documents by key efficiently in a new database, improving performance for larger datasets.
- **Database Operations** : By loading documents into a separate database, operations can distribute across multiple cores, enhancing performance.
- **Practical Use** : This technique is useful for various **data analysis tasks** , particularly when detailed sorting and aggregation are needed beyond simple view queries.

couchdb-lucene: Full-Text Indexing and More

Overview

While simple sorting and exporting methods are effective for basic tasks, couchdb-lucene offers a powerful solution for comprehensive indexing. This section explores how to leverage Lucene for full-text indexing , along with other capabilities like sorting by value and indexing geolocations.

What is Lucene?

- **Lucene** is a high-performance, **Java-based search engine library** designed for full-text indexing.
- It is commonly used to integrate **keyword search functionalities** into applications.

What is couchdb-lucene?

- **couchdb-lucene** acts as a **web service wrapper** around Lucene's core features, enabling it to index documents from CouchDB.
- It runs as a standalone **Java Virtual Machine (JVM)** process and communicates with CouchDB over **HTTP** . This allows you to run it on a separate machine if necessary.

Key Points on Usage

- This section will provide a brief example to help you get started with couchdb-lucene for full-text indexing.
- If full-text indexing is not currently a requirement for your work, you can skip this section and return later.

Alternative Method for Text-Based Indexing

- You can create a simple mapping function to associate keywords with documents. Example: python Copy code

```
def tokenizingMapper ( doc ): tokens = doc.split() for token in tokens: if isInteresting(token): #
Filter out stop words, etc. yield token, doc
```
- However, to implement effective **Information Retrieval (IR)** concepts and scoring functions for ranking documents by relevance, it's advisable to use couchdb-lucene instead of developing your own solution.

Note on Implementation

- This section will utilize **httplib** to interact directly with CouchDB's **REST API** and will include JavaScript view functions, offering a different approach compared to previous sections that used the CouchDB module.

Conclusion

Using couchdb-lucene is beneficial for full-text indexing and more complex tasks that go beyond basic frequency analysis. Its robust capabilities make it a preferred choice for implementing effective search and indexing solutions.

Installing and Configuring couchdb-lucene

Overview

Binary snapshots and installation instructions for couchdb-lucene can be found at [GitHub](#) . This includes configuration details in the README file.

Installation Steps

1. **Prerequisites** : Ensure **Java** is installed on your system.
2. **Run Script** : Execute the `run` script provided with couchdb-lucene. This will:
 - Start a web server.
 - Modify CouchDB's `local.ini` configuration file to enable communication between couchdb-lucene and CouchDB over **HTTP** .

Key Configuration Changes

Refer to the README for specific configurations, but key settings include:

- **Timeout Setting** : Increase the timeout value to allow for longer operations:

ini Copy code `[couchdb] os process_timeout = 300000 ; Set timeout to 5 minutes.`

- **External Hook** : Define a custom behavior for full-text indexing (fti):

ini Copy code `[external] fti =/path/to/python /path/to/couchdb-lucene/tools/couchdb-external-hook.py [httpd db_handlers] fti = {couch httpd_external , handle external_req , << "fti" >>}`

This configuration allows the `fti` context to trigger the **couchdb-external-hook.py** script, which then communicates with the Java process running Lucene for indexing.

Windows Users

Windows users should be aware that a service wrapper for couchdb-lucene may be obsolete as of October 2010. Check the discussion thread for more information: [Apache Server Discussion](#) .

Performing Indexing

Once couchdb-lucene is configured and running, you can execute the following script (Example 3-12) to perform default indexing on the Subject field and the content of documents in a database:

python Copy code

```
# -*- coding: utf-8 -*- import sys import httplib from urllib import quote import json DB = sys.argv[ 1 ] QUERY = sys.argv[ 2 ]
```

Query Capabilities

With full-text indexing on the subject and content of each message:

- You can use **Lucene query syntax** for detailed searches.
- Default keyword search capabilities are usually sufficient for basic needs.

Summary

Installing and configuring couchdb-lucene enables powerful full-text indexing and search capabilities for your CouchDB documents. Proper configurati

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Creating a JavaScript-Based Design Document for couchdb-lucene

Overview

To utilize couchdb-lucene for full-text indexing, you will create a design document that defines indexing functions in JavaScript. This document allows you to index your CouchDB documents by specific fields, such as Subject and Content .

Design Document Structure

The design document (dd) will look like this:

javascript Copy code

```
dd = { 'fulltext' : { 'by subject' : { 'index' : "function(doc) { var ret = new Document(); ret.add(doc.Subject); return ret; }" }, 'by content' : { 'index' : "function(doc) { var ret = new Document(); for (var i = 0; i < doc.parts.length; i++) { ret.add(doc.parts[i].content); } return ret; }" } } }
```

- **by subject** : Indexes the **Subject** field of each document.
- **by content** : Indexes the **content** of all parts within each document.

Creating the Design Document

To create the design document in CouchDB, you can use a PUT request. The equivalent command in the terminal would be:

bash Copy code


```
$ curl -X PUT http://localhost:5984/DB/ design /lucene -d @dd.json
```

In Python, you can achieve this as follows:

python Copy code

```
import httplib import json import sys try : conn = httplib.HTTPConnection( 'localhost' , 5984 ) conn.request( 'PUT' ,
'%s/ design /lucene' % (DB,), json.dumps(dd)) response = conn.getresponse() finally : conn.close() if
response.status != 201 : # Created print ( 'Unable to create design document: %s %s' % (response.status,
response.reason)) sys.exit()
```

Querying the Design Document

Once the design document is created, you can query it using the `fti` HTTP handler specific to couchdb-lucene. The request format is:

bash Copy code

```
$ curl http://localhost:5984/DB/ fti / design /lucene/by subject ?q=QUERY
```

In Python, you can make a GET request like this:

python Copy code

```
try : conn.request( 'GET' , '%s/ fti / design /lucene/by subject ?q=%s' % (DB, quote(QUERY))) response =
conn.getresponse() if response.status == 200 : response_body = json.loads(response.read()) print
(json.dumps(response_body , indent= 4 )) else : print ( 'An error occurred fetching the response: %s %s' %
(response.status, response.reason)) finally : conn.close()
```

Summary

To use couchdb-lucene effectively:

- Create a design document with full-text indexing functions.
- Use HTTP requests to store the design document and query it.
- The document should include an index for specific fields like **Subject** and **Content** to enable efficient searching.

For detailed instructions and f

Overview

couchdb-lucene allows for efficient full-text indexing of CouchDB documents using Lucene's powerful capabilities. When a query is executed, the results include document IDs that you can use to retrieve the original documents from CouchDB for further analysis.

Document Object

- The **Document object** is defined by **couchdb-lucene**, not CouchDB. This object structure is essential when creating the index.

Sample Query Results

For example, if you query for the term "raptor" in the Enron dataset, you might get a response like the one shown below:

json Copy code

```
{ "etag": "11b7c665b2d78be0", "fetch_duration": 2, "limit": 25, "q": "default:raptor", "rows": [ { "id": "3b2c340c28782c8986737c35a355d0eb", "score": 1.4469 }, { "id": "3b2c340c28782c8986737c35a3542677", "score": 1.3902 }, { "id": "3b2c340c28782c8986737c35a357c6ae", "score": 1.3759 }, /* ... output truncated ... */ { "id": "2f84530cb39668ab3cdab83302e56d65", "score": 0.8108 } ], "search_duration": 0, "skip": 0, "total_rows": 72 }
```

Key Elements of the Response

- **etag**: Unique identifier for the response version.
- **fetch duration**: Time taken to fetch results.
- **limit**: Maximum number of results returned.
- **q**: The query term used.
- **rows**: Contains the results, each with an **id** (document identifier) and **score** (relevance score).
- **total rows**: Total number of documents matching the query.

Accessing Documents

- The **id** values in the response can be used to look up the corresponding documents in CouchDB. This enables further analysis of the documents related to the search term.

Data Flow

You don't interact with couchdb-lucene directly. Instead, you:

1. Define a **design document** with specific fields for full-text indexing.

2. Issue a query to CouchDB, which recognizes the **fulltext** and **fti** terms from the design document and handles the request appropriately.

Scoring Documents

- The scoring of documents returned by Lucene is based on complex algorithms, discussed in Lucene's scoring documentation, particularly the **Similarity class**.
- Customizing Lucene's scoring properties typically requires source code modifications, but you can influence scoring through query parameters.

Conclusion

Using couchdb-lucene simplifies the process of full-text indexing in CouchDB, enabling efficient searching and retrieval of documents based on their content. For detailed configuration and customization options, refer to the official couchdb-lucene documentation.

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Using couchdb-lucene for Enhanced Search Capabilities

Boosting Relevance

- You can enhance search results by using the **"boost"** parameter via the **couchdb-lucene** API instead of modifying source code. This allows for flexible ranking of documents based on their relevance to search queries.

Contextualizing Search Results

- For example, when searching for **"raptor"** related to the Enron scandal, the top-ranked message might provide important context:
 - It discusses quarterly valuations for assets within the **Raptor structure**, noting that several parties were involved in the valuation process.
- This context can guide you effectively when sifting through thousands of messages.

Exploring Conversation Threads

- To understand discussions surrounding topics like **Raptor**, you can analyze message threads. Starting with basic

string heuristics on the **Subject** header can help identify related messages.

- More advanced methods involve examining the **Message-ID** , **In-Reply-To** , and **References** headers to accurately piece together conversations.
- A popular algorithm for this is **jwz threading** , named after its creator, **Jamie Zawinski** . This method provides a structured way to parse message threads.

Implementation of jwz Threading

- The jwz threading algorithm takes various message attributes into account, allowing for effective threading of email conversations.
- A modified version of this algorithm, initially found in the **Mail Trends** project, has been adapted for more object-oriented code and JSON-compatible input/output formats, resulting in better memory efficiency.
- While the original Mail Trends project hasn't seen updates since 2008, its foundational principles remain relevant for email analysis.

Workflow Overview

- The overall workflow for implementing threading will involve using the jwz algorithm to connect related messages based on key headers and structure.

Conclusion

Using couchdb-lucene not only enhances your search capabilities with relevance boosting but also facilitates deeper analysis of email conversations through effective threading techniques.

Creating Discussion Threads from mbox Data with jwz Threading

Overview

This script demonstrates how to create discussion threads from mbox data using the jwz threading algorithm. It reads emails from a CouchDB database, processes them to identify threads, and then writes the threaded data back into a new CouchDB database.

Key Components

- **Libraries Used :**

- `couchdb` : For interacting with the CouchDB database.
- `mailboxes _jwzthreading` : Implements the jwz threading algorithm and the **Message** class for email objects.
- `mailboxes _CouchDBBulkReader` : Custom class for efficiently reading multiple documents from CouchDB.
- `datetime` : For measuring execution time.
- `PrettyTable` : For formatting output (though not explicitly shown here).
- `jsonlib2` or `json` : For handling JSON data.

Script Breakdown

1. Setup :

- The database name is passed as a command-line argument.
- A recommended number of processing threads (`NUM PROC_THREADS`) is set to optimize performance, ideally about one thread per core.

2. Bulk Reading from CouchDB :

- A **CouchDBBulkReader** instance is created to efficiently read data.
- The script measures and prints the time taken to read documents from CouchDB.

3. Threading in Memory :

- The emails are converted into **Message** objects and processed with the **thread** function to group related messages into threads.
- Execution time for this step is also recorded and printed.

4. Writing Threading Info to CouchDB :

- A new database is created to store the threaded messages.
- The script writes the threading results back to CouchDB. Since CouchDB handles writes in a serialized manner, threading won't significantly speed this operation.
- The time taken for the bulk writing operation is printed.

5. Basic Statistics :

- The total number of threads identified is printed for reference.
- Optionally, the script could calculate the length of each thread and store that information, either in this script or as a simple reducer in CouchDB.

Conclusion

This example showcases how to effectively utilize jwz threading to organize mbox email data into discussion threads, improving the analysis of email conversations. The use of bulk reading and writing optimizes performance when working with potentially large datasets in CouchDB.

Overview

This section describes how to analyze discussion threads created from email messages. It highlights the process of reading messages from CouchDB, performing threading, and storing the results in a separate database. Additionally, it includes generating basic statistics about the length of these threads.

Key Steps

1. Collecting Statistics :

- The script sorts the threading results based on thread length using: `python Copy code stats = sorted (zip ([result[1] for result in results], [len (t) for t in threads]), key= lambda x: x[1])`
- This creates a list of tuples containing the thread ID and its corresponding length.

2. Displaying Results :

- A **PrettyTable** is used to format and display the statistics: `python Copy code fields = ['Thread Id' , 'Thread Length'] pt = PrettyTable(fields=fields)`
- Each thread's ID and length are added as rows to the table, which is then printed.

3. Data Flow :

- The overall process involves:
 - **Bulk Reading** : Messages are retrieved from CouchDB.
 - **Threading in Memory** : The retrieved messages are processed to create threads.
 - **Writing to a New Database** : Each thread is stored as a document in a separate CouchDB database, maintaining references to the original messages.

4. Thread Document Example :

- Each thread is represented as a document in CouchDB. For instance: `json Copy code { " id " : "b6d4f96224bc546acd34c405e6fff62f" , " rev " : "1-1bf63dcdd94067ad647afe2ea3ade63c" , "thread" : [{ "external id " : "24a30d62545728e26eb3311d63ae6e02" , "subject" : "FW: Sitara EOL Bridge Problem Today" } , { "external id " : "bb808c9081912f5861295bf1d105dd02" , "subject" : "FW: Sitara EOL Bridge Problem Today" } , { "external id " : "3b2c340c28782c8986737c35a332cd88" , "subject" : "FW: Sitara EOL Bridge Problem Today" }] }`

5. Useful Libraries :

- **mailboxes jwzthreading** : This library converts message documents into a format suitable for the threading algorithm. It handles the core threading logic and outputs the results in JSON format, which can be easily ingested back into CouchDB.
- **CouchDBBulkReader** : This utility is used to efficiently read multiple documents from CouchDB.

6. Alternative Approaches :

- While the current method uses a straightforward threading process, it's possible to apply a **map/reduce** approach to calculate statistics about thread lengths, as described in earlier sections.

Conclusion

This workflow effectively demonstrates how to extract and analyze email conversation threads using CouchDB and the jwz threading algorithm. The combination of these tools allows for efficient management and insightful anal

Optimizing Data Retrieval with CouchDBBulkReader

Overview

The CouchDBBulkReader is a specialized tool designed to enhance the performance of data retrieval from CouchDB by using multi-threading. It allows multiple read requests to be processed simultaneously, significantly speeding up the operation compared to standard methods.

Key Points

1. Performance Advantage :

- **CouchDBBulkReader** leverages an **internal thread pool** to handle multiple requests concurrently. This is especially beneficial because CouchDB, by default, utilizes only a single core for each read or write request.
- This design choice, while seemingly counterintuitive given Erlang's concurrency capabilities, is intentional for stability and reliability.

2. Thread Management :

- The reader fetches document **ID values** first, which is a lightweight operation. These IDs are then sorted and divided into chunks.
- Each chunk is assigned to a separate thread, which retrieves the full documents for its designated range.

3. Thread Pool Guidelines :

- It is recommended to use **one processing thread per core** to optimize performance without overwhelming the system.
- Monitoring tools (e.g., **top** on Unix, **Task Manager** on Windows) should be used to assess system performance during operation. Ideally, the **beam.smp** process for CouchDB should show high CPU utilization (around 200% on a dual-core machine).

4. Efficiency Observation :

- The majority of the time spent in the operation is during the **bulk read**, while the threading and writing of the thread documents back to CouchDB take minimal time.
- An interesting exercise is to explore implementing the threading logic within a **map/reduce** framework or rewriting it in **JavaScript**.

5. Thread Pool Package :

- The **threadpool** package, necessary for CouchDBBulkReader, can be installed using: bash Copy code
`easy install threadpool`

6. Future Improvements :

- While bulk write operations in CouchDB are unlikely to support multi-core usage due to serialization to disk, there's potential for improvements in read operations, especially since the underlying data structure (a tree) can be traversed at multiple nodes.

Conclusion

The CouchDBBulkReader significantly improves data retrieval efficiency by employing a multi-threading approach. This allows for better resource utilization and faster access to

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Using a Thread Pool to Maximize Read Throughput from CouchDB

Overview

The CouchDBBulkReader class is designed to efficiently read documents from CouchDB using a thread pool . This approach enhances read performance by allowing multiple threads to retrieve data simultaneously.

Key Components

1. Class Initialization :

- The constructor (`__init__`) takes parameters:
 - `db` : Name of the database.
 - `num_threads` : Number of threads to use for reading.
 - `host` and `port` : Default to 'localhost' and 5984 .
- It initializes essential attributes and fetches document IDs using `getDocIds` () .

2. Thread Pool Setup :

- A **thread pool** is created with the specified number of threads.
- **Requests** are generated using `threadpool.makeRequests()` , which sets up the tasks for fetching documents. The `getDocs` method retrieves the documents, while `callback` and `errCallback` handle the results and errors, respectively.
- Each request is added to the thread pool using `self.pool.putRequest(req)` .

3. Reading Documents :

- The `read` method manages the execution of the thread pool:
 - It enters a loop, checking periodically (every 0.5 seconds) for the completion of tasks.
 - If there are no results pending, it returns the collected results.
 - Handles keyboard interrupts gracefully, allowing for a controlled exit.

4. Document ID Retrieval :

- The `getDocIds` () method is responsible for quickly fetching all document IDs from the database. This data is then sorted and distributed among the threads for efficient processing.

Summary

The CouchDBBulkReader class effectively enhances data retrieval from CouchDB by utilizing a thread pool to manage multiple concurrent read requests. This design allows for improved through

Functions for Managing Document Retrieval in CouchDB

1. `getDocIds ()` Method

The `getDocIds ()` method retrieves all document IDs from a CouchDB database.

- **Purpose :**
 - To gather document IDs efficiently and prepare them for further processing.
- **Key Steps :**
 - **Partitioning :** A helper function, `partition`, divides a list of IDs into chunks. It uses specified indices to create sublists for even distribution across threads.
 - **HTTP Request :**
 - A connection is established to the CouchDB server.
 - A GET request is sent to the endpoint `/_all_docs` to fetch all documents.
 - If the response status is not `200 (OK)`, it prints an error message and exits.
 - **ID Extraction :**
 - The method collects IDs from the response while filtering out any that start with an underscore (which are typically CouchDB's internal documents).
 - The collected IDs are sorted for consistent partitioning.
 - **Partitioning IDs :**
 - The number of IDs is divided by the number of threads (`num_threads`) to determine the size of each partition.
 - The `partition` function is called to split the sorted IDs into evenly sized chunks, which will be processed by different threads.

2. `getDocs ()` Method

The `getDocs ()` method fetches document data based on a list of provided IDs.

- **Purpose :**
 - To retrieve the full documents associated with specified IDs.
- **Key Steps :**
 - **Define Range :** The method identifies the starting and ending keys from the provided ID list.
 - **HTTP Request :**
 - A connection is made to CouchDB, and a GET request is sent using the range defined by `startkey` and `endkey`, including the actual document data (`include_docs =true`).
 - Again, if the response status is not `200 (OK)`, it prints an error message and exits.
 - **Return Data :** The method returns the raw response data containing the document details.

3. `errCallback ()` Method

The `errCallback ()` method handles errors that occur during document retrieval.

- **Purpose :**
 - To manage error reporting when a request fails.
- **Key Steps :**
 - It prints an error message that includes the request details and the result, then exits the program.

Summary

These methods form an essential part of the `CouchDBBulkReader` class, enabling efficient retrieval and handling of document IDs and their corresponding content from CouchDB. The design promot

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`callback ()` Method

The `callback ()` method processes results from the CouchDB requests.

- **Purpose :**
 - To handle the results of document retrieval requests and store them for further use.
- **Key Steps :**
 - It reads the JSON response from the request.
 - The method extracts the `rows` from the result.
 - It then appends each document (`row['doc']`) to the `self.results` list for later access.

Analyzing Discussion Threads with Enron Data

After establishing the ability to compute discussion threads, we turn our focus back to the Enron data .

Goal :

To identify and organize participants in discussions that mention the term Raptor .

Desired Output Structure

The ideal data structure to capture the findings looks like this:

json Copy code

```
{ "participants": [ "person-1@example.com", "person-2@example.com", ... ], "message_ids": [ "id1", "id2", ... ], "subject": "subject" }
```

Steps to Achieve This

1. Query CouchDB-Lucene :

- Perform a search for message IDs that contain the term **Raptor** .

2. Look Up Discussion Threads :

- For each message ID returned from the query, retrieve the associated discussion threads.

3. Compute Unique Email Addresses :

- Extract unique email addresses from the header fields (e.g., From, To, CC) of the messages in these threads.

Implementation

Example 3-18 will illustrate how to implement these steps using previous code components. This method enables comprehensive analysis of discussions related to specific terms, effectively connecting participants and their messages.

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Example 3-18: Threading Discussion Threads from mbox Data

This code demonstrates a method for organizing participants in email discussions, specifically focused on the Enron dataset.

Overview

- **Purpose** : To query and analyze discussion threads based on specified keywords, extracting participants' email addresses and related message IDs.

Key Components

1. Imports :

- Libraries used include `sys` , `httplib` , `urllib` , and `json` .

2. Database and Query Setup :

- `DB` : Specifies the database to query, in this case, **Enron** .
- `QUERY` : The search term provided via command line (e.g., "Raptor").

Querying CouchDB-Lucene

- The code queries CouchDB-Lucene for relevant message IDs using two index types: **by subject** and **by content** .

python Copy code

```
message_ids_of_interest = [] for idx in ['by subject ', 'by content ']: ...
```

- **Connection** : Establishes an HTTP connection to CouchDB.
- **Request** : Sends a request to fetch messages matching the **QUERY** .
- **Response Handling** :
 - If successful (status 200), it extracts message IDs and appends them to `message_ids_of_interest` .
 - If an error occurs, it prints the error message and exits.

Removing Duplicates

- The code converts `message_ids_of_interest` into a set and back to a list to eliminate duplicates.

python Copy code

```
message_ids_of_interest = list ( set (message_ids_of_interest ))
```

Fetching Discussion Threads

- The script retrieves discussion thread data from a separate database, which stores threads related to the original messages.

python Copy code

```
try : conn = httplib.HTTPConnection( 'localhost' , 5984 ) conn.request( 'GET' , '/%s/ all_docs ?include docs =true' % (DB + '-threads' , )) ...
```

- **Response Handling** :
 - On success, it constructs a list of threads containing their IDs and associated message IDs.

python Copy code

```
threads = [dict([( 'thread_id ', row['doc'][( 'id ')]), ( 'message_ids ', [t[ 'external_id ' ] for t in row['doc'][( 'thread' )]])
for row in json.loads(response.read())['rows'] ]]
```

Conclusion

This approach efficiently aggregates discussion threads related to a specified term, preparing the data for further analysis of participants and their interactions within th

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Finding Relevant Discussion Threads and Extracting Participants

This section outlines the process of identifying relevant discussion threads based on specific message IDs and extracting unique email addresses from those threads.

Key Steps

1. Filtering Threads of Interest :

- The code searches for threads that contain message IDs matching those fetched from the **Lucene index** .

```
python Copy code threads_of_interest = [t for t in threads for message_id in t[ 'message_ids' ] if message_id in message_ids_of_interest ]
```

2. Removing Duplicates :

- To eliminate duplicate threads, the code uses a list called `seen` to keep track of thread IDs.

```
python Copy code seen = [] idx = 0 while idx < len (threads_of_interest ): if threads_of_interest [idx][ 'thread_id ' ] in seen: threads_of_interest .pop(idx) else : seen.append(threads_of_interest [idx][ 'thread_id ' ]) idx += 1
```

3. Collecting Message IDs for Threads of Interest :

- The script gathers all message IDs from the filtered threads.

```
python Copy code message_ids_for_threads_of_interest = [t[ 'message_ids ' ] for t in threads_of_interest ]
```

4. Flattening and Removing Duplicates :

- It then flattens the list of message IDs and removes any duplicates to create a unique list.

```
python Copy code message_ids_for_threads_of_interest = list ( set ([message_id for message_id in message_ids_for_threads_of_interest for message_id in message_ids ]))
```

5. Querying CouchDB for Full Document Details :

- A **bulk request** is made to CouchDB to fetch full documents that correspond to the unique message IDs.

```
python Copy code try : conn = httpplib.HTTPConnection( 'localhost' , 5984 ) post_params = json.dumps({ 'keys' : message_ids_for_threads_of_interest } ) conn.request( 'POST' , '/%s/all_docs ?include_docs =true' % (DB, ), post_params ) ... finally : conn.close()
```

6. Parsing Email Addresses :

- With the complete message data available, the script extracts the **From** header to compile a list of

participants for each thread.

```
python Copy code for thread in threads_of_interest : participants = [] for message_id in
thread[ 'message_ids ' ]: doc = [d for d in full_docs if d[ 'id ' ] == message_id ][
0 ] try : participants.append(doc.get( 'From' ))
```

Summary

This process effectively narrows down relevant discussion threads, eliminates duplicates, and gathers unique email addresses of participants based on specified criteria. This can lead to valuable insights about the conversations surrounding specific topics, such as "Raptor" in the context of the Enron emails.

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Extracting Participants from Email Threads

This section outlines how to extract email participants from various header fields in the messages of interest and compile a structured output.

Key Steps

1. Extending Participants List :

- The script extracts email addresses from the **To** , **Cc** , and **Bcc** fields of each message.

```
python Copy code participants.extend(doc.get( 'To' )) if doc.get( 'Cc' ):
participants.extend(doc.get( 'Cc' )) if doc.get( 'Bcc' ): participants.extend(doc.get( 'Bcc' ))
```

2. Handling Exceptions :

- A try-except block is used to handle potential errors, such as missing standard headers. If an email is not found in the expected fields, the process continues without interruption.

```
python Copy code except : pass # Maybe a X-To header, etc. as opposed to To?
```

3. Removing Duplicates :

- The list of participants is converted to a set and back to a list to ensure uniqueness, preventing duplicate email addresses.

```
python Copy code thread[ 'participants' ] = list ( set (participants))
```

4. Storing Subject :

- The subject of the thread is also captured from one of the documents.

```
python Copy code thread[ 'subject' ] = doc[ 'Subject' ]
```

5. Outputting Results :

- Finally, the structured data for each thread is printed in a formatted JSON output.

```
python Copy code print json.dumps(threads_of_interest , indent= 4 )
```

Sample Output Explanation

The output from the script provides a clear view of the discussions related to the search query "Raptor." Each entry includes:

- **thread_id** : A unique identifier for the discussion thread.
- **participants** : A list of email addresses involved in the conversation.
- **message_ids** : IDs of messages that are part of the thread.
- **subject** : The subject line of the email thread.

Example Output :

json Copy code

```
[{"thread_id": "b6d4f96224bc546acd34c405e6c471c5", "participants": ["j.kaminski@enron.com", "rakesh.bharati@enron.com"], "message_ids": ["24a30d62545728e26eb3311d63effb47"], "subject": "FW: Note on Valuation"}, {"thread_id": "b6d4f96224bc546acd34c405e6dbc0d4", "participants": ["mary.fischer@enron.com", "danny.wilson@enron.com", "a.lee@enron.com", "john.swafford@enron.com", "facundo.caminos@enron.com"], "message_ids": ["24a30d62545728e26eb3311d633cf6b3"], "subject": "Tax Accruals on the Raptor Companies"}, ...]
```

Conclusion

This structured approach allows for effective analysis of email communications, focusing on participants and subjects within specific discussions. The ou

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Overview of Mail Conversation Analysis and Visualization

The script discussed enables the identification of participants in email conversations based on keywords, streamlining the process of gathering this information. While it is possible to manually search through an mbox file in a mail client, this automated approach offers efficiency and adaptability for various analyses.

Key Points:

1. Automated Participant Identification :

- The script uses a **keyword heuristic** to determine who participated in specific conversations, facilitating quick insights into discussions without manual searching.

2. Visualization of Mail Data :

- Various methods exist to visualize email data, such as:
 - **Bar charts** to analyze the volume of messages over time.
 - **Graphs** showing connections between senders and recipients, filtered by discussion threads.
 - **Timelines** to track message queries over time.

3. SIMILE Timeline Tool :

- The **SIMILE Timeline** is highlighted as a powerful visualization tool for event-centric data, especially useful for email analysis. It allows users to view each message as a unique event and larger discussions as extended events over time.
- Each message can be linked so that clicking it in the timeline opens the full message in **Futon** , enhancing the user experience.

4. Pragmatic Approach to Visualization :

- Instead of building a comprehensive web application, the focus is on modifying the script output to generate **JSON** compatible with the SIMILE Timeline. This requires minimal effort and enables quick visualization.
- The output format must adhere to the structure expected by the SIMILE Timeline, as shown in Example 3-20.

Example Output Format for SIMILE Timeline :

The expected JSON format includes:

- **dateTimeFormat** : Specifies the date format (e.g., "iso8601").
- **events** : An array of event objects, each containing:
 - **start** : The timestamp for when the message was sent.
 - **description** : A brief note about the message, often including participants.
 - **link** : A URL linking to the full message in the mail database.
 - **durationEvent** : A boolean indicating if the event has a duration (typically false for single messages).
 - **title** : A title for the event, summarizing its content.

Sample Event Structure :

json Copy code

```
{ "dateTimeFormat": "iso8601", "events": [ { "start": "2002-02-06T08:20:49-08:00", "description": "Message involving sarah.palmer@enron.com", "link": "http://localhost:5984/ _utils /document.html?enron/bb...", "durationEvent": false, "title": "Enron Mentions -- 02/06/02" }, { "start": "2001-05-22T16:20:25-07:00", "description": "Message involving j.kaminski@enron.com, ...", "title": "Enron Mentions -- 05/22/01" } ] }
```

Conclusion

This approach to analyzing and visualizing email data not only simplifies the identification of participants in discussions but also provides a user-friendly way to explore mail events through visualization tools like the SIMILE Timeline. With minimal adjustments, rich visual representat

Overview of Augmented Output for SIMILE Timeline

To visualize email discussions using the SIMILE Timeline, an augmented output is created to include events for both individual messages and discussion threads. This enables a comprehensive representation of email interactions.

Key Components :

1. Event Structure :

- Each event represents either a **discussion thread** or an **individual message** .
- The event includes:
 - **title** : Subject of the email.
 - **start** : The date and time the message was sent, formatted in ISO 8601.
 - **durationEvent** : A boolean indicating that the event does not have a duration (typically set to false).
 - **description** : A summary that lists the participants involved in the message.
 - **link** : A URL pointing to the full message in the database.

2. Creating Events :

- For each thread, the script processes all related messages:
 - It gathers participants' email addresses from the **From** , **To** , **Cc** , and **Bcc** headers.
 - It captures the **date** of each message for timeline visualization.
 - An **event** object is constructed for each message, which is then appended to an events list.

3. Data Parsing :

- The script parses the date using the `parse()` function to ensure it is formatted correctly for the timeline.
- If a message lacks certain headers, it gracefully handles exceptions to avoid errors.

4. Output Example :

- Each event generated would look like this:

```
json Copy code { "link" : "http://localhost:5984/  utils  /document.html?enron/24a..." ,  
"durationEvent" : false , "title" : "RE: Pricing of restriction on Enron stock" }
```

5. Date Range for Threads :

- After processing messages within a thread, the script can determine the **start** and **end dates** based on the dates of the messages, which is useful for visualizing the timeline of discussions.

Summary :

The augmentation process for output from Example 3-18 involves creating detailed event objects for individual messages in addition to discussion threads. This allows for a richer and more informative visualization of email interactions using the SIMILE Timeline, enabling better insights into communication patterns w

Creating Events for Discussion Threads in SIMILE Timeline

Event Structure for Threads :

1. Event Object Creation :

- Each thread generates an **event** object.
- **Title** : Set to the **subject** of the thread (`doc['Subject']`).
- **Start and End Dates** :
 - The **start date** is the earliest message date in the thread.
 - The **end date** is the latest message date in the thread.
 - Dates are formatted in **ISO 8601** .
- **Duration Event** : Set to **true** , indicating that the event spans multiple messages.
- **Description** : Includes the total number of messages in the thread.

2. Appending Events :

- Each constructed thread event is added to the `events` list.

Output Preparation :

1. Directory Check :

- The script checks for an existing directory named `out` . If it doesn't exist, it creates one.

2. Data File Creation :

- The events data is written to a file named `simile_data.json` in the `out` directory.
- The file contains the `dateFormat` set to **ISO 8601** and the list of events, formatted with indentation for readability.

3. Confirmation Message :

- The script prints a message indicating the location of the data file.

Visualizing with SIMILE Timeline :

- The SIMILE Timeline can be pointed to the `simile_data.json` file to visualize the email data.
- There are various online resources and tutorials available to help users get started with the SIMILE Timeline, including a tutorial titled "Getting Started with Timeline."

Summary :

This process effectively prepares and formats email data for visualization in SIMILE Timeline, allowing for interactive exploration of email discussions. The example demonstrates the foundational steps needed to visualize threaded conversations based on email data, setting the stage for mor

Analyzing Your Own Mail Data

Why Analyze Your Mail Data?

- While the **Enron mail data** serves as a good example for mail analysis, analyzing your own mail data can provide more relevant insights.

Exporting Mail Data :

1. Using Mail Clients :

- Many popular email clients offer an “**export to mbox**” option, which simplifies getting your mail data into a format suitable for analysis.
- For instance, in **Apple Mail** :
 - Select messages.
 - Go to **File > Save As...** and choose “**Raw Message Source**” to export as an mbox file.
- This method is commonly supported in most major mail clients.

2. Automating Mbox Creation :

- If you use an online mail client, you can either download your data into a desktop mail client or automate mbox file creation.
- Most online mail services support:
 - **POP3 (Post Office Protocol version 3)**
 - **IMAP (Internet Message Access Protocol)**
- You can create Python scripts to fetch your mail data.

Using Command-Line Tools :

- **getmail** : A robust command-line tool for downloading mail data from various sources.
 - Written in Python, it's easy to set up and use.
 - To download data from **Gmail** :
 - Install getmail.
 - Create a **getmailrc** configuration file with basic settings.
- **Python Libraries** :
 - Two standard libraries, **poplib** and **imaplib** , provide a solid foundation for creating scripts to pull down mail data.
 - Searching online will yield numerous useful scripts for these libraries.

Example Configuration :

- For a *nix environment, Example 3-22 includes settings for a getmailrc file.
- **Windows Users** : Adjust the [destination] path and [options] message_log values to valid paths for your system.

Conclusion :

By util

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Sample getmail Settings for a *nix Environment

getmail Configuration Example :

- Below is a sample configuration for getmail, which allows you to retrieve emails using IMAP.

plaintext Copy code

```
[retriever] type = SimpleIMAPSSLRetriever server = imap.gmail.com username = ptwobrussell password = blarty-  
blar-blar [destination] type = Mboxrd path = /tmp/gmail.mbox [options] verbose = 2 message_log =  
~/getmail/gmail.log
```

Key Sections of the Configuration :

- **[retriever] :**
 - **type** : Defines the method for retrieving emails, here it uses **SimpleIMAPSSLRetriever** .
 - **server** : The IMAP server address, e.g., `imap.gmail.com` .
 - **username** : Your Gmail username.
 - **password** : Your Gmail password (consider using app passwords for security).
- **[destination] :**
 - **type** : Specifies the output format as **Mboxrd** .
 - **path** : The file path where the emails will be saved, e.g., `/tmp/gmail.mbox` .
- **[options] :**
 - **verbose** : Sets the verbosity level for logging.
 - **message_log** : Path to the log file for recording email retrieval details.

Using getmail :

- To run getmail and retrieve your emails, simply execute the command in your terminal:

bash Copy code

```
$ getmail
```

- This will download your emails to the specified mbox file. The output will indicate the number of messages retrieved.

Further Reading :

- The section titled “**Tapping into Your Gmail**” (page 231) explains using the **imaplib** Python library to download Gmail data for analysis.
- **Graph Your Inbox Chrome Extension** :
 - A tool that analyzes webmail. Install the extension, authorize it, and run Gmail queries.
 - You can search for keywords, time values, or specific senders, making it user-friendly for analyzing your inbox.

Advanced Techniques :

- If you're looking to delve deeper than headers and into text mining, the **smtplib** module allows for more advanced email content analysis.

This summary gives you the necessary config

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Closing Remarks

In this chapter, we explored the basics of analyzing mail data , particularly focusing on mbox files, which are a simple and portable format suitable for analysis using Python tools.

Key Takeaways :

- **Mboxes** :
 - A convenient format for storing emails, making them easy to analyze and share.
- **Open Source Tools** :
 - There is a wealth of **open source technology** available for mining mbox data, allowing for extensive analysis.
- **Python's Role** :
 - Python is an excellent language for working with mbox files, offering numerous libraries and packages for processing email data.
- **Data Sharing** :

- Utilizing tools like **CouchDB** facilitates easy data sharing and enhances collaboration.

This chapter serves as a s

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CHAPTER 4: Twitter—Friends, Followers, and Setwise Operations

Overview of Twitter : Twitter is a microblogging service where users can share short updates (up to 140 characters). It has significantly changed how people communicate online.

Key Analytic Functions :

This chapter introduces basic analytical functions that can be implemented using the Twitter APIs to explore various questions, including:

- **Friends and Followers :**
 - How many **friends** (accounts you follow) and **followers** (accounts following you) do you have?
- **Unreciprocated Relationships :**
 - Who are you following that **is not following you back** ?
 - Who is following you that you **are not following back** ?
- **Network Friendliness :**
 - Identify the **friendliest** and **least friendly** people in your network.
- **Mutual Friends :**
 - Who are your **mutual friends** (people you follow who also follow you)?
- **Potential Influence :**
 - Assess your potential influence based on your followers and their followers, particularly in terms of **retweets** .

Important Note :

The Twitter API is continually evolving, so it's essential to follow the ****@TwitterAP**

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Chapter Overview

This chapter focuses on analyzing relationships among Twitter users (Twitterers), while the next chapter will examine the content of tweets . The code developed in this chapter is designed to handle common issues, such as:

- **Twitter rate limits** : Restrictions on the number of API requests.
- **Network I/O errors** : Issues related to network input/output.
- **Large data volumes** : Managing and processing large amounts of data.

The outcome is a command-line utility that can be customized for personal use, available at [GitHub](#) .

Importance of Tools

Having the right tools to harvest and mine your tweets is crucial. There are ongoing initiatives to archive historical Twitter data in the U.S. Library of Congress, which may alleviate some challenges related to data harvesting and API limitations. Additionally, firms like Infochimps are emerging, offering various types of Twitter data, from archived tweets to analyses of user behavior.

RESTful and OAuth APIs

In 2010 , Twitter evolved significantly by transitioning to OAuth for authentication, enhancing documentation, and improving API transparency. Key changes include:

- The collapse of the **Twitter search APIs** into the traditional **REST API** .
- The increased use of **streaming APIs** for production environments.

This chapter focuses on the following Twitter API functions:

- **Social graph APIs** : Retrieve friends and followers of a user.
- **Extended user information API** : Access details like name, location, and last tweet for a list of users.
- **Tweet data API** : Gather information about tweets.

While there's a wealth of information available online, this chapter aims to cover only what is necessary.

Python Client

The Python client used for Twitter analysis is simply called `twitter` . It provides a minimal wrapper around the Twitter API,

facilitating interactions with Twitter data.

Rate Limits

- **OAuth requests** : Limited to **350 requests per hour** .
- **Anonymous requests** : Limited to **150 requests per hour** .

These limits are generally adequate for most applications; if they aren't, it may indicate a need to rethink the application design.

Future Expectations

As of December 2010, Twitter implements OAuth 1.0a , with expectations of

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Using Twitter's RESTful API

The Twitter API utilizes RESTful web services , allowing users to construct requests similar to how URLs are formed in Twitter's documentation. For example, to retrieve user information for Tim O'Reilly, you would use the following curl command :

bash Copy code

```
$ curl 'http://api.twitter.com/1/users/show.json?screen_name=timoreilly'
```

What is curl?

- **curl** is a command-line tool for transferring data between a client and a server using various protocols, especially HTTP.
- It is included by default in most *nix systems, but **Windows users** may need to download and configure it.

Request Details

1. **Versioned API** : The URL includes `/1` , indicating that **Version 1** of the API is being used.
2. **Parameters** : You can use either `user_id` or `screen_name` to specify the user. In this example, `screen_name` is used.

Python Equivalent

The equivalent Python code to fetch the same user information is shown in Example 4-1 :

python Copy code

```
# -*- coding: utf-8 -*- import twitter import json screen_name = 'timoreilly' t = twitter.Twitter(domain='api.twitter.com', api_version='1') response = t.users.show(screen_name=screen_name) print(json.dumps(response, sort_keys=True, indent=4))
```

Authentication Notes

- The `/users/show` API call **does not require authentication** . However, it may behave differently if a user has set their tweets to **protected** in privacy settings.
- The `/users/lookup` API is similar but requires **authentication** and allows batch lookups by accepting a **comma-separated list** of `screen_name` or `user_id` .

Understanding OAuth

OAuth stands for "open authorization" and is an essential part of interacting with Twitter's API. This section introduces OAuth 2.0 , which is the next generation of the authorization scheme:

- **Future Plans** : Twitter intends to support OAuth 2.0, similar to what Facebook has already implemented.
- Le

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Understanding OAuth in Twitter API

OAuth is a widely adopted authorization framework that allows applications to access user data without needing to share usernames and passwords. As of this book's writing, Twitter supports OAuth 1.0a , but there are plans for a transition to OAuth 2.0 .

Key Features of OAuth

- **Three-Legged Authorization** : Both OAuth 1.0a and OAuth 2.0 involve three parties:
 - **Client Application** : The app requesting access to data.

- **Resource Owner** : The service (like Twitter) that holds the user's data.
- **End User** : The individual who grants access to their data.

This process is often referred to as a "dance," as it involves several steps of communication.

Benefits of OAuth

- **Security** : Users do not share their credentials directly with the client application, reducing the risk of password theft.
- **User Experience** : OAuth simplifies the authorization process, making it more user-friendly.

OAuth Workflow Overview

1. **User Intent** : The user wants to authorize a client application to access certain data (referred to as a **scope**) managed by a web service.
2. **Redirection for Authorization** : Instead of asking for a password, the client redirects the user to the resource owner (e.g., Twitter) to authorize the requested scope.
 - The client identifies itself using a unique **client identifier** and provides a contact method for post-authorization.
3. **Authorization Confirmation** : If the user approves the request, the client receives an **authorization code** that confirms their authorization.
4. **Access Token Exchange** :
 - The client then presents the authorization code, along with its client identifier and a **client secret** , to the resource owner.
 - This process ensures that the resource owner can verify the client.

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Understanding OAuth 2.0 Access Tokens

In OAuth 2.0 , the access token plays a crucial role in allowing client applications to make requests on behalf of users. Here are the key details:

1. **Access Token Characteristics** :
 - The access token may be **short-lived** , meaning it will expire after a certain period.
 - Clients may need to **refresh** the access token to maintain access without requiring user reauthorization.
2. **Usage** :
 - The client uses the access token to perform actions and make requests until it is either **revoked** by the user or **expires** .
3. **Workflow Overview** :

- The OAuth 2.0 process involves several steps that start with the web client, as depicted in the web server flow (see **Figure 4-1**). The process follows a sequence (labeled A to E) that ensures the client ends up back at the web client after completion.

Understanding the OAuth 2.0 Specification

- As of late 2010, the OAuth 2.0 specification is still being finalized, with various details under discussion.
- For a comprehensive understanding, it is recommended to:
 - **Read the OAuth spec** thoroughly.
 - **Sketch out flows** and scenarios to visualize the process.
 - **Role-play** different user perspectives, including malicious scenarios.

Single-User Use Case

- Twitter provides a **streamlined option** for “single-user use cases,” allowing simpler access to credentials without implementing the entire OAuth flow. More information on this can be found at Twitter’s developer documentation.

Conclusion

This chapter assumes familiarity with the standard OAuth flow, which is essential for effective interaction with Twitter’s API and other web services that utilize OAuth 2.0. Understanding these

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A Lean, Mean Data-Collecting Machine

Fetching data from Twitter is straightforward: you make a request , store the response , and repeat. However, several real-world challenges can complicate this process, including:

- **Network I/O issues**
- The notorious **fail whale** (indicating Twitter is down)
- **API rate limits** (which restrict the number of requests you can make)

To effectively manage these challenges, it’s essential to plan ahead and consider potential problems.

Writing Robust Code

When running a long program that consumes your rate limit, it's crucial to write robust code that can:

- Handle **exceptional conditions** that may occur.
- Attempt to **remedy** any issues.
- **Save state** to resume operations later if necessary.

You should expect unexpected situations while collecting data from Twitter; these challenges are often more common than anticipated.

Key HTTP Errors to Handle

When collecting Twitter data, you might encounter two frequent HTTP errors :

1. **401 Error** (Not Authorized): This occurs when trying to access protected user data.
2. **503 Error** (Over Capacity): This error arises unpredictably when Twitter is overwhelmed.

Whenever Twitter returns an error, the twitter module raises a TwitterHTTPError exception, which can be managed using a try/except block in Python.

Example Code for Data Harvesting

To effectively gather friend data while managing exceptions, you'll need to create a Twitter app to obtain a consumer key and secret. This process is quick and easy.

Here's a minimal code example demonstrating how to authenticate using OAuth and collect friend data, while handling common exceptions:

python Copy code

```
# -*- coding: utf-8 -*- import sys import time import cPickle import twitter
```

This code serves as a foundation that you

This script is designed to fetch a list of friend IDs from a specific Twitter user. Here's a breakdown of how it works:

Step-by-Step Breakdown

1. Import Required Functionality :

- The script starts by importing the necessary function from the `twitter.oauth_dance` module to handle the OAuth process.

2. Setup Credentials :

- You need to create a Twitter app to get your **consumer key** and **consumer secret** . These will allow you to authenticate your application.
- Define the `SCREEN_NAME` as the first command-line argument, which specifies whose friends you want to fetch.
- Set a limit on the number of friends to fetch (`friends_limit = 10000`).

3. Authenticate with OAuth :

- Use the `oauth_dance` function to obtain the **OAuth tokens** required for authentication.
- Initialize the Twitter API client with the necessary authentication details.

4. Initialize Variables :

- Create an empty list, `ids` , to store the friend IDs.
- Set an initial **wait period** of 2 seconds and a `cursor` variable to manage pagination.

5. Fetch Friend IDs :

- Use a `while` loop to continuously fetch friend IDs until the cursor indicates there are no more friends to retrieve (`cursor != 0`).
- If the wait period exceeds 1 hour (3600 seconds), save any collected data to disk and exit.

6. Handle API Requests :

- Inside the loop, try to call the `friends.ids` API to get friend IDs.
- If successful, extend the `ids` list with the retrieved IDs and reset the wait period.
- If a **TwitterHTTPError** occurs:
 - **401 Error** : The user's tweets are protected.
 - **502 or 503 Errors** : Indicates a temporary issue; wait and retry.
 - If the **rate limit** is reached, calculate the time until the limit resets and sleep for that duration.

7. Cursor Management :

- Update the `cursor` to the next cursor value from the response to continue fetching in the next iteration.

8. Output the Results :

- Print the number of fetched IDs for the specified user.

Example Code

Here's the essential code for this operation:

python Copy code

```
from twitter.oauth_dance import oauth_dance import sys import time import cPickle import twitter # Twitter app
credentials consumer_key = "consumer_secret" = "SCREEN_NAME = sys.argv[1] friends_limit = 10000 #
Authenticate (oauth_token, oauth_token_secret) = oauth_dance ('MiningTheSocialWeb', consumer_key,
consumer_secret) t = twitter.Twitter(domain='api.twitter.com', api_version = '1', auth=twitter.oauth.OAuth(oauth
token, oauth_token_secret, consumer_key, consumer_secret)) ids = [] wait_period = 2 # seconds cursor = -1 while
cursor != 0 : if wait_period > 3600 : # 1 hour print ('Too many retries. Saving partial data to disk and exiting') with
open ('%s.friend_ids' % str(cursor), 'wb') as f: cPickle.dump(ids, f) exit() try : response = t.friends.ids(screen_name
```

```
=SCREEN NAME , cursor=cursor) ids.extend(response['ids']) wait_period = 2 except twitter.api.TwitterHTTPError as e: if e.e.code == 401 : print ( 'Encountered 401 Error (Not Authorized)' ) print ( 'User %s is protecting their tweets' % (SCREEN NAME ,)) elif e.e.code in ( 502 , 503 ): print ( 'Encountered %i Error. Trying again in %i seconds' % (e.e.code, wait_period )) time.sleep(wait_period ) wait_period *= 1.5 continue elif t.account.rate_limit_status ()['remaining_hits'] == 0 : status = t.account.rate_limit_status () now= time.time() # UTC when rate_limit_resets = status['reset_time_in_seconds'] # UTC sleep_time = when rate_limit_resets - now print ( 'Rate limit reached. Trying again in %i seconds' % (sleep_time ,)) time.sleep(sleep_time ) continue cursor = response['next_cursor'] print ( 'Fetched %i ids for %s' % ( len (ids), SCREEN NAME )) if len (ids) >= friends_limit : break
```

Summary

This script illustrates a robust approach to collecting Twitter data while handling common issues like authentication, API errors, and rate limits effectively. It ensures data integrity by saving partial results.

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Key Notes on Collecting Twitter Friend IDs

This section discusses how to work with Twitter's API to collect friend IDs using OAuth, as well as some important details about the process.

Storing OAuth Tokens

- The `twitter.oauth` module includes functions like `read_token_file` and `write_token_file`. These functions help you **store** and **retrieve** your OAuth token and secret, eliminating the need to enter a PIN every time you authenticate.

Terminology Clarification

- In the context of OAuth:
 - The term “**client**” in OAuth 2.0 is equivalent to “**consumer**” in OAuth 1.0.
 - This is reflected in variable names such as `consumer_key` and `consumer_secret` used in the script.

Important Points to Note

1. Obtaining Consumer Keys :

- To get your own `consumer_key` and `consumer_secret`, you must register an application on [Twitter](#).

[Developer](#). These credentials allow your application to access your Twitter account data.

2. Fetching Friend IDs :

- When requesting friend or follower data, the API can return up to **5,000 IDs per call** . If more than 5,000 IDs exist, a **cursor** value (not equal to zero) is returned to fetch the next batch.
- The example provided sets a limit of **10,000 IDs** , but you can increase this limit as needed.

3. Rate Limits :

- Regular Twitter accounts can potentially retrieve up to **1,750,000 IDs** before hitting the rate limit of **350 requests per hour** . While most users won't have this many friends, popular accounts often have significantly more followers.

Example Output

- The script will ultimately print the collected **IDs** of friends, allowing you to process or analyze them as needed.

Summary

This section provides a concise overview of how to manage OAuth authentication, collect Twitter friend IDs, and understand the constraints of the Twitter API, including rate l

Key Notes on Twitter API Data Order and Refactoring Code

Understanding ID Values Order

- **ID Values** : The IDs returned from Twitter's API, particularly from requests like `t.friends.ids` , appear to be in **reverse chronological order** . This means:
 - The **first ID** is the person you most recently followed.
 - The **last ID** corresponds to the first person you followed.
- This pattern also applies to requests for followers, where `t.followers.ids` returns results in the same order.

Introduction to Twitter APIs

- You've been introduced to only a few **Twitter APIs** , which are capable of answering various questions about your account or any public account. However, there are many more APIs available for exploration.

Refactoring Example Code

Purpose of Refactoring

- To make your code cleaner and more efficient, especially when dealing with repetitive tasks like OAuth authentication and API requests. This ensures that your code is robust and maintainable.

Refactored Code Overview

- The refactored version of Example 4-2 is shown as Example 4-3, which implements a more structured approach:
 - **Isolation of OAuth Logic** : The logic for logging in and making API requests is separated into functions: `login()` and `makeTwitterRequest()` .
 - This structure allows for easier management of the OAuth process and makes the overall code cleaner.

Example Code Snippet

python Copy code

```
# -*- coding: utf-8 -*- import sys import time import cPickle import twitter from twitter import login from twitter
_util import makeTwitterRequest friends_limit = 10000 t = login() # Authenticate with Twitter def getFriendIds ( screen
_name = None , user_id = None , friends_limit = 10000 ): assert screen_name is not None or user_id is not None
ids = [] cursor = - 1 while cursor != 0 : params = dict ( cursor=cursor ) if screen_name is not None : params[ 'screen
name ' ] = screen_name else : params[ 'user_id ' ] = user_id response = makeTwitterRequest( t , t.friends.ids ,
**params )
```

Summary

This section highlights the order of ID values returned from Twitter's API and introduces a refactored coding approach that improves the management of OAuth and API requests. By establishing clear patterns and functions, you can make your code more efficient

Key Notes on Fetching Twitter IDs and Using Redis

Fetching Friend IDs

- The code continues by extending the list of **IDs** with those retrieved from the response: python Copy code


```
ids.extend(response[ 'ids' ]) cursor = response[ 'next_cursor' ]
```

- After fetching, it prints the number of IDs collected for the specified user: python Copy code

```
print >> sys.stderr, 'Fetched %i ids for %s' % ( len (ids), screen_name or user_id )
```
- If the count of fetched IDs reaches the **friends_limit** (set to 10,000), the loop breaks: python Copy code

```
if len (ids) >= friends_limit : break return ids
```

Main Function Execution

- The main section of the script runs the function **getFriendIds** using a command-line argument: python Copy code

```
if __name__ == '__main__': ids = getFriendIds(sys.argv[ 1 ], friends_limit = 10000 ) print ids # Output the fetched IDs
```

Utility Modules

- The examples will consistently use **twitter_login** and **twitter_util** modules to maintain clarity and simplicity in code.
- It's beneficial to explore the source of these utility modules online, as they will be frequently referenced and will contain various convenient functions.

Introduction to Redis

What is Redis?

- **Redis** is described as a powerful **data structures server** that is popular due to its **performance** and **simplicity**.

Data Management Considerations

- When collecting large amounts of data, consider how to store and manage that data efficiently.
- Initially, you might think of saving data directly to disk. However, this can lead to complex directory structures that are hard to navigate: markdown Copy code

```
./ screen_name1 / friend_ids.json follower_ids.json user_info.json screen_name2 / ...
```
- If a user has many friends or followers, this structure can become unwieldy, resulting in:
 - **Millions of subdirectories** that are difficult to manage.
 - Performance issues when generating directory listings for vast numbers of files.

Challenges with Data Storage

- Storing data on disk requires keeping track of all screen names, as retrieving directory listings for millions of files can be inefficient

Key Notes on Using Redis for Data Management

Challenges with File Storage

- **File Locking Issues** : When multiple processes attempt to write to the same file simultaneously, you must manage **file locking** , which complicates data handling.
- **Key/Value Storage Needs** : A more efficient solution is to use a system that allows easy storage of **key/value pairs** , similar to a **disk-backed dictionary** .

Example of Key Construction

- Keys can be constructed by combining a **user ID** , a **delimiter** , and a **data structure name** : python Copy code `s = {} s["screen_name1 $friend_ids "] = [1 , 2 , 3 , ...]`
- Accessing the data is straightforward: python Copy code `s["screen_name1 $friend_ids "]` # Returns `[1, 2, 3, ...]`

Desired Functionality

- It would be beneficial to perform **set operations** automatically, such as: python Copy code `s.intersection("screen_name1 $friend_ids " , "screen_name1 $follower_ids ")`
- This would allow you to find **mutual friends** (friends who also follow back).

Introduction to Redis

- **Redis** is an open-source data structure store that can perform the desired set operations.
- **Features** :
 - **Fast and Scalable** : Written in C, making it very efficient.
 - **Active Maintenance** : Regular updates and community support.
 - **Great Python Client** : Provides comprehensive documentation and easy access to its features.

Installation and Usage

1. Install Redis :

- Start by downloading and running the Redis server. For Windows, consider using a precompiled binary from servicestack.net.
- Install the Python client using: bash Copy code `easy_install redis`

2. Basic Redis Operations :

- Here's how the earlier Python example translates to Redis code:

```
python Copy code import redis r = redis.Redis(host= 'localhost' , port= 6379 , db= 0 ) # Using default parameters [ r.sadd( "screen    name1    $friend    ids    " , i) for i in [ 1 , 2 , 3 , ...] ] r.smembers( "screen    name1    $friend    ids    " ) # Returns [1, 2, 3, ...]
```

- **sadd** and **smembers** are set operations that allow adding and retrieving members from a set.

Data Structures and Operations

- Redis supports various data structures (sets, lists, hashes) and offers specific operations tailored to each.
- Set operations are particularly valuable for addressing common questions related to social interactions on platforms like Twitter.

Additional Resources

- To better understand Redis's capabilities, refer to the **documentation for the Redis Python client** .
- For technical insights, check out the section “Redis: under the hood” for an in-depth look at its internal workings.

Summary

Redis simplifies the management of large datasets with efficient key/value storage, fast operations, and robust functionality for

Elementary Set Operations

Overview of Sets and Lists

- **Sets** : Unordered collections that contain only unique members.
- **Lists** : Ordered collections that can include duplicates.
- Python, since **Version 2.6** , supports sets with the built-in `set` data structure.

Common Set Operations

Here are the fundamental set operations you will often use:

1. **Union (\cup)** : Combines two sets, returning all unique members.
 - **Example :**
 - **Friends** = {Abe, Bob}
 - **Followers** = {Bob, Carol}
 - Result: **Friends \cup Followers** = {Abe, Bob, Carol}
2. **Intersection (\cap)** : Returns members that are present in both sets.
 - **Example :**
 - Result: **Friends \cap Followers** = {Bob}
 - Indicates mutual friends.
3. **Difference ($-$)** : Returns members present in one set but not in the other.
 - **Example :**
 - **Friends – Followers** : {Abe}
 - Indicates people being followed who do not follow back.
 - **Example :**
 - **Followers – Friends** : {Carol}
 - Indicates people following who are not being followed back.

Redis Set Operations

Redis offers built-in functions for performing set operations, making it easy to handle relationships like friends and followers. Here are some relevant Redis commands:

- **smembers** : Returns all members of a set.
- **scard** : Returns the number of members in a set (cardinality).
- **sinter** : Computes the intersection of multiple sets.
- **sdiff** : Computes the difference of multiple sets.
- **mget** : Retrieves a list of values for given keys.
- **mset** : Stores values against keys.
- **sadd** : Adds an item to a set (creating the set if it doesn't exist).
- **keys** : Returns keys matching a specified pattern.

Conclus

Analyzing Set Theory: A Historical Perspective

Introduction to Set Theory

- **Georg Cantor** is credited with the formalization of **set theory** in his 1874 paper titled "On a Characteristic

Property of All Real Algebraic Numbers.” His work focused on understanding **infinity** and various types of numbers.

Key Questions in Set Theory

Cantor addressed important questions regarding different sets of numbers:

1. Are there more **natural numbers** (0 and positive integers) than **integers** (positive and negative)?
2. Are there more **rational numbers** (numbers expressible as fractions) than integers?
3. Are there more **irrational numbers** (numbers that cannot be expressed as fractions, e.g., π , $\sqrt{2}$) than rational numbers?

Cardinality of Sets

- Cantor's findings showed that the **cardinalities** (sizes) of sets like natural numbers, integers, and rational numbers are all **countably infinite**. This means they can be put into a sequence that extends infinitely in one direction.
- The cardinality of a countably infinite set is denoted as \aleph_0 (aleph-null).

Examples of Countably Infinite Sets

Patterns for various sets that demonstrate countable infinity:

- **Natural Numbers** : 0, 1, 2, 3, 4, ...
- **Positive Integers** : 1, 2, 3, 4, 5, ...
- **Negative Integers** : -1, -2, -3, -4, -5, ...
- **Integers** : 0, 1, -1, 2, -2, 3, -3, 4, -4, ...
- **Rational Numbers** : Formed as fractions, represented in a spiral on the Cartesian plane. Although some fractions are undefined (like 0/0), this doesn't affect the overall cardinality.

Irrational Numbers and Their Cardinality

- The set of **irrational numbers** cannot be counted like the previous sets. Cantor's **diagonalization argument** proves that you can never create a one-to-one correspondence to map them back to a countable set.
- This means there are infinitely more irrational numbers than can be matched to the countably infinite sets, leading to the conclusion that the cardinality of irrational numbers is greater than \aleph_0 .

Conclusion

Cantor's exploration of set theory laid the groundwork for modern mathematics, highlighting the complexity of infinity and the relationships between different types of numbers. Understanding these concepts is essential for analyzing data st

Understanding Cardinality of Irrational Numbers

Cardinality and Power Sets

- The **cardinality** of the set of **irrational numbers** is not countably infinite like the sets of natural numbers, integers, and rational numbers.
- It is shown that the **power set** of a set with cardinality \aleph_0 (countably infinite) corresponds to the cardinality of the set of all irrational numbers, known as \aleph_1 .
- Further, the power set of the set with cardinality \aleph_1 is referred to as \aleph_2 , and this pattern continues.

Power Sets

- A **power set** includes all possible subsets of a given set. Understanding power sets, especially for infinite sets, can be complex but is a significant concept in set theory.

Enhancing Data Processing with Redis

Utilizing Redis for Twitter Data

- **Redis** is ideal for efficiently processing and analyzing large volumes of Twitter data, particularly for certain types of queries.
- By adapting previous code examples, you can store and compute basic **friend** and **follower** metrics using Redis.

Example Code Overview

The following outlines the core components of the example for collecting and analyzing Twitter data:

- **Import Required Libraries** : The code imports necessary modules such as `sys`, `locale`, `time`, `twitter`, and `redis`.
- **Login to Twitter** : The `login()` function is used to

Connecting and Analyzing Twitter Data with Redis

Establishing a Redis Connection

- Connect to a **Redis** instance using default settings: python Copy code `r = redis.Redis()`

Wrapping Functions for Friends and Followers

- Create function wrappers to simplify calls to get friends and followers:
 - `getFriends` : A partial function binding for retrieving friend IDs.
 - `getFollowers` : A partial function binding for retrieving follower IDs.

python Copy code

```
getFriends = functools.partial( getFriendsOrFollowersUsingFunc , t.friends.ids, 'friend_ids ', t, r) getFollowers =  
functools.partial( getFriendsOrFollowersUsingFunc , t.followers.ids, 'follower_ids ', t, r)
```

Retrieving Data

- Use the screen name to fetch friends and followers: python Copy code

```
screen_name = SCREEN_NAME print  
>> sys.stderr, 'Getting friends for %s...' % (screen_name , ) getFriends(screen_name ,  
limit=MAXINT) print >> sys.stderr, 'Getting followers for %s...' % (screen_name , )  
getFollowers(screen_name , limit=MAXINT)
```

Computing Metrics with Redis

- Use Redis to compute various metrics:
 - **Number of Friends** : python Copy code `n_friends = r.scard(getRedisIdByScreenName(screen_name , 'friend_ids '))`
 - **Number of Followers** : python Copy code `n_followers = r.scard(getRedisIdByScreenName(screen_name , 'follower_ids '))`
 - **Friends Not Following Back** : python Copy code `n_friends_diff_followers = r.sdiffstore('temp'
, [getRedisIdByScreenName(screen_name , 'friend_ids '), getRedisIdByScreenName(screen_name , 'follower_ids ')]) r.delete('temp')`
 - **Followers Not Following Back** : python Copy code `n_followers_diff_friends = r.sdiffstore(
'temp' , [getRedisIdByScreenName(screen_name , 'follower_ids '),
getRedisIdByScreenName(screen_name , 'friend_ids ')]) r.delete('temp')`
 - **Mutual Friends** : python Copy code `n_friends_inter_followers = r.sinterstore('temp' ,
[getRedisIdByScreenName(screen_name , 'follower_ids '), getRedisIdByScreenName(screen_name , 'friend_ids ')]) r.delete('temp')`

Displaying Results

- Print the computed metrics: `python` Copy code

```
print '%s is following %s' % (screen_name, locale.format('%d', n_friends, True))
print '%s is being followed by %s' % (screen_name, locale.format('%d', n_followers, True))
print '%s of %s are not following %s back' % (locale.format('%d', n_friends_diff_followers, True), locale.format('%d', n_friends, True), screen_name)
print '%s of %s are not being followed back by %s' % (locale.format('%d', n_followers_diff_friends, True), locale.format('%d', n_followers, True), screen_name)
```

This structured approach allows efficient retrieval and analysis of Twitter friends and followers using Redis, making it easier to c

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Analyzing Twitter Followers with Redis

Displaying Mutual Friends

- The number of **mutual friends** for a user is printed as follows: `python` Copy code

```
print '%s has %s mutual friends' % (screen_name, locale.format('%d', n_friends_inter_followers, True))
```

Functionality Overview

- The code uses `functools.partial` to create `getFriends` and `getFollowers` functions from a common base function. This makes the code more concise and reusable.

Data Persistence in Redis

- In **Example 4-4**, there's no explicit call to `r.save`. This means that data persistence is controlled by **redis.conf**, which schedules when data is saved to disk.
- **Redis** primarily stores data in memory and takes **asynchronous snapshots**. This means there's a risk of losing data during unexpected events (like crashes or power outages).
- To protect against data loss, it's highly recommended to enable the `appendonly` option in `redis.conf`. This option helps create an "append-only" file that records changes, ensuring better data safety.

Example Output

- When analyzing Tim O'Reilly's network, the output might look like this:
 - timoreilly is following 663
 - timoreilly is being followed by 1,423,704
 - 131 of 633 are not following timoreilly back
 - 1,423,172 of 1,423,704 are not being followed back by timoreilly
 - timoreilly has 532 mutual friends

Rate Limiting Considerations

- Be aware of the **rate limit** of **350 OAuth requests per hour** . For Tim O'Reilly, about **300 API calls** may be necessary to gather all follower IDs, making the total run time slightly under an hour.
- If collecting a smaller number of followers to avoid hitting the rate limit, understand that:
 - The API documentation does not guarantee randomness in the data sampled.
 - Followers are returned in **reverse chronological order** , which may skew results if you only take the first N pages.

Implications for Popular Accounts

- For very popular users, like **Britney Spears** with over **5,000,000 followers** , it may take around **1,000 API calls** over approximately **four hours** to fetch all followers.
- Using **Twitter-streaming APIs** can help keep data current, so you won't need to repeatedly pull large datasets.

This structured approach ensures that you can effectively analyze Twitter follower dynamics while being mindful of the technical li

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Importance of Sample Size in Analysis

Key Concept

- A common mistake in analysis is neglecting the **overall size of a population** compared to your **sample size** . For instance, if you randomly sample **10,000** of Tim O'Reilly's **friends** , you cover his entire friends list, but this represents only a small portion of his **followers** .

Statistical Significance

- The relationship between sample size and population size is crucial for determining:
 - **Statistical significance** of results.
 - The **confidence level** you can have in your findings.

Interesting Analysis Questions

- Basic statistics may lead to deeper questions, such as:
 - **Who are the 131 people not following Tim O'Reilly back?**
 - Understanding who isn't following back can provide insights into a person's **interests**.

Resolving User IDs to Screen Names

Enhancing User Information Retrieval

- Instead of analyzing a list of user IDs, it's more engaging to convert these IDs into actual **user objects**. This is achieved through an enhanced version of Example 4-4.

Example 4-5 Overview

- The code in **Example 4-5** adds reusable **error-handling** code and provides functionality to resolve user IDs to **screen names** using the **/users/lookup API**.

Code Snippet Breakdown

python Copy code

```
# -*- coding: utf-8 -*- import sys import json import redis from twitter_login import login from twitter_util import
getUserInfo if __name__ == "__main__": screen_names = sys.argv[1:] # Accepts a list of screen names from
command line t = login() # Log in to Twitter API r = redis.Redis() # Connect to Redis print json.dumps(getUserInfo(t, r,
screen_names=screen_names), # Fetch user info indent= 4 # Pretty print the JSON output )
```

Summary

- Understanding the population size relative to your sample is essential for valid analysis.
- Resolving user IDs to screen names enhan

Overview of the getUserInfo Function

Purpose

- The `getUserInfo` function retrieves user information from Twitter using the **/users/lookup API** and stores it in **Redis** for easy access.

Function Breakdown

python Copy code

```
def getUserInfo ( t, r, screen_names ): info = [] # Initialize an empty list to store user info response =
makeTwitterRequest(t, t.users.lookup, screen_name = ','.join(screen_names ) # Join screen names into a single
string ) for user_info in response: # Store user information in Redis under two different keys r. set
(getRedisIdByScreenName(user_info ['screen_name '], 'info.json'), json.dumps(user_info )) # By screen name r.
set (getRedisIdByUserId(user_info ['id'], 'info.json'), json.dumps(user_info )) # By user ID info.extend(response) #
Append user info to the list return info # Return the collected user info
```

Key Points

- **Dual Key Storage :**
 - The function saves user information using both **user ID** and **screen name** as keys.
 - This allows easy lookup between the two, which is crucial because Twitter's social graph APIs return only user IDs.
- **Utility of User ID to Screen Name Mapping :**
 - Converting a user ID to a screen name is essential since the data from Twitter often comes in ID form, lacking intuitive context.
- **Storage Considerations :**
 - Although this method involves redundant data storage, the convenience of quick lookups makes it worthwhile.
 - If storage is a concern, a more efficient approach could be taken.

Example User Object

- Below is an example of a user information object for **Tim O'Reilly** , represented in **JSON** format:

json Copy code

```
{ "id": 2384071, "verified": true, "profile_sidebar_fill_color": "e0ff92", "profile_text_color": "000000", "followers
count": 1423326, "protected": false, "location": "Sebastopol, CA", "profile_background_color": "9ae4e8", "status":
{ "favorited": false,
```

User Data Overview for Tim O'Reilly

Sample Tweet Data

- **Text** : "AWESOME!! RT @adafruit: a little girl asks after seeing adafruit ..."
- **Created At** : Sun May 30 00:56:33 +0000 2010
- **Source** : Seismic (via web)
- **ID** : 15008936780
- **Coordinates** : null (no geographical coordinates provided)
- **In Reply To** : None (not a reply tweet)
- **Place** : null (no specific place tagged)
- **Geo** : null (no geolocation data)

User Profile Information

- **Name** : Tim O'Reilly
- **Screen Name** : timoreilly
- **Description** : Founder and CEO of O'Reilly Media; interested in "alpha geeks"
- **URL** : [O'Reilly Radar](#)
- **Profile Image** :
- **Background Image** :
- **Profile Link Color** : #0000ff (blue)
- **Profile Sidebar Border Color** : #87bc44 (green)
- **Created At** : Tue Mar 27 01:14:05 +0000 2007
- **UTC Offset** : -28800 (Pacific Time)
- **Time Zone** : Pacific Time (US & Canada)
- **Statuses Count** : 11,220 (total tweets)
- **Friends Count** : 662 (number of friends followed)
- **Followers Count** : Data not provided in this snippet
- **Favourites Count** : 10 (number of favorited tweets)
- **Geo Enabled** : true (location services enabled)
- **Notifications** : false (not receiving notifications)
- **Following** : false (not following back)

Error Handling and Rate Limits

HTTP Error Handling

- The `handleTwitterHTTPError` function manages HTTP errors but does not cover every possible error. This design choice allows flexibility in how to respond based on the situation (e.g., network issues).

Data Retrieval Challenges

- **Batch Data Retrieval** : User data is fetched in batches of up to 100 IDs.
 - **Good News** : Accessing user IDs provides valuable information, including profiles and latest tweets.
 - **Not-So-Good News** : Due to Twitter's rate limits:
 - For Tim O'Reilly's friends, only **7 API calls** are needed.
 - For followers, it requires **over 14,000 API calls** , taking nearly **two days** to collect all data,

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Random Sampling and Statistical Significance with Redis

- **Random Sampling** : You can perform random sampling on the **friends** and **followers** of any Twitter user. By collecting all ID values, you can analyze them for statistical significance.
- **Redis Function** : The `srandmember` function in Redis allows you to get a random member from a specified set. For example, using `srandmember(timoreilly$followers ids)` returns a random follower ID.

Computing Common Friends and Followers

- **Common Connections** : Identifying common friends and followers between Twitter users can reveal shared interests. Users who follow many of the same accounts may have similar preferences or connections.
- **Set Operations** : Finding common friends and followers is achieved using set operations in Redis.

Example: Finding Common Friends and Followers

Code Example (friends_followers_friends_followers_in_common .py)

python Copy code

```
import sys
import redis
from twitter_util import getRedisIdByScreenName
pp, r = redis.Redis()

def friendsFollowersInCommon(screen_names):
    # Store common friends in a temporary set
    r.sinterstore('temp$friends_in_common',
        [getRedisIdByScreenName(screen_name, 'friend_ids') for screen_name in screen_names])
    # Store common followers in a temporary set
    r.sinterstore('temp$followers_in_common',
        [getRedisIdByScreenName(screen_name, 'follower_ids') for screen_name in screen_names])
    # Print the number of common friends
    print('Friends in common for %s: %s' % (' '.join(screen_names), pp(r.scard('temp$friends_in_common'))))
```

Output Explanation

- The function `friendsFollowersInCommon` :
 - Computes common friends using `sinterstore` to create a temporary set of shared friends.
 - Computes common followers similarly.
 - Uses **pretty-printing** for cleaner output, ma

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Analyzing Common Followers and Friends

- **Output Common Followers** : The function prints the number of common followers for the specified users:

```
python Copy code print ( 'Followers in common for %s: %s' % ( ', ' .join(screen_names ),
pp(r.scard( 'temp$followers in_common ' )))
```

- **Cleanup Temporary Data** : After processing, the temporary sets created to store common friends and followers are deleted to free up resources:

```
python Copy code r.delete( 'temp$friends in_common ' ) r.delete( 'temp$followers in_common ' )
```

- **User Input** : The script checks if at least two screen names are provided as command-line arguments. If not, it prints an error message and exits:

```
python Copy code if len (sys.argv) < 3 : print >> sys.stderr, "Please supply at least two screen
names." sys.exit( 1 )
```

Note on Screen Names

- It's assumed that the provided screen names have already been added to Redis. Users can refer to the previous scripts for this setup.

Sampling Information

- The `randomkey` function in Redis can be used to sample friends and followers. You can then use the `getUserInfo` function to retrieve useful information like screen names, recent tweets, and locations.

Measuring Influence on Twitter

- **Influence Definition** : Influence can be gauged by how far information spreads, particularly through retweets. The more followers a user has, the higher the potential for their tweets to be shared.
- **High Retweet Rates** : Users whose tweets are frequently retweeted are considered more influential. Those who share many retweets, even if they aren't their original tweets, may be categorized as **mavens** —people well-connected and eager to share information.

- **Comparing Influence** : A simple method to measure influence is by comparing the number of followers among users. More followers indicate a greater potential audience for tweets.

Extracting Follower Information

- The number of friends and followers can be easily obtained using the `/users/lookup` and `/users/show` APIs. The following snippet demonstrates how to extract this information: python Copy code

```
for screen_name in screen_names:
    json = json.loads(r.get(getRedisIdByScreenName(screen_name, "info.json")))
    n_friends, n_followers = json['friends_count'], json['followers_count']
```

Conclusion

Understanding common connections and measuring influence on Twitter can provide valuable insights into user interactions and the potential impact of shared information. Using Redis for data manageme

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Expanding Analysis Beyond Follower Counts

- **Influence Beyond Numbers** : Simply counting followers is not enough to measure influence. A user might not be as popular as someone like **Tim O'Reilly** , but having him as a follower can greatly extend your reach if he retweets your content. This can connect you to a broader audience.
- **Breadth-First Approach** : To better assess a user's potential influence, consider exploring their network beyond just follower counts. Use a **breadth-first search (BFS)** approach, which allows you to examine connections several levels deep.

Crawling Friends and Followers

- **Crawl Function** : Example 4-8 presents a **crawl function** that takes a list of screen names and allows for adjustable **crawl depth** . This function also has parameters for controlling the number of friends and followers retrieved.
- **Parameters Explained** :
 - `friends_limit` : Maximum number of friends to retrieve (default: **10,000**).
 - `followers_limit` : Maximum number of followers to retrieve (default: **10,000**).
 - `depth` : How many levels deep to crawl into the network.
 - `friends_sample` : Fraction of friends to sample (default: **20%**).
 - `followers_sample` : Fraction of followers to sample (default: **0%**).

Example Code: Crawling Friends and Followers

python Copy code

```
# Import necessary libraries import sys import redis import functools from twitter _login import login from twitter _util
import getUserInfo from twitter _util import getFriendsOrFollowersUsingFunc # Set up user login and Redis connection
SCREEN_NAME = sys.argv[1] t = login() r = redis.Redis() # Create convenience functions for getting friends and
followers getFriends = functools.partial( getFriendsOrFollowersUsingFunc , t.friends.ids, 'friend_ids ', t, r) getFollowers =
functools.partial( getFriendsOrFollowersUsingFunc , t.followers.ids, 'follower_ids ', t, r) def crawl ( screen_names , friends
limit = 10000 , followers limit = 10000 , depth= 1 , friends sample = 0.2 , followers sample = 0.0 ): getUserInfo(t, r,
screen_names =screen_names ) for screen_name in screen_names : # Additional logic for crawling goes here...
```

Conclusion

Using a breadth-first approach to crawl friends and followers provides deeper insights into a user's influence and network dynamics. By retrieving and analyzing data at multiple levels, you can better understand how con

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Crawling Friends and Followers

- **Gathering Friend and Follower IDs :**
 - Use the `getFriends` function to retrieve a list of friend IDs for a given **screen name** with a specified limit (`friends limit`).
 - Use the `getFollowers` function to get follower IDs for the same screen name with a specified limit (`followers limit`).
- **Fetching User Information :**
 - Retrieve detailed user information for both friends and followers using the `getUserInfo` function, which takes the list of IDs and a sampling fraction (`friends sample` and `followers sample`).
- **Building a Queue for Depth Crawling :**
 - Combine the screen names of friends and followers into a **next queue** .
 - Use a loop to increase the depth (`d`) until it reaches the specified **depth** .
 - For each screen name in the current queue, fetch their friends and followers, adding them to the next queue.

Random Sampling

- The `sample` parameter allows you to fetch a random subset of nodes, helping manage the number of nodes processed at each level of the graph.

Main Functionality

- The script starts by checking if a screen name has been provided. If not, it prompts the user to supply one.
- After executing the `crawl` function, the gathered data can be used for further analysis, such as calculating influence metrics.

Example Code Snippet for Calculating Average Influence

python Copy code

```
# Import necessary libraries import sys import json import locale import redis # Sample code continues here to pull data from Redis and calculate influence...
```

Analyzing Influence

- Once you have crawled enough friends and followers, you can calculate metrics like the **average number of followers** at one level out.
- Y

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Notes on Twitter Follower Analysis with Redis

Imports and Setup:

- **PrettyTable:** Used for formatting output in a readable table.
- **Twitter Utility Functions:**
 - `pp` : Pretty print function for numbers.
 - `getRedisIdByScreenName` : Generates a consistent Redis ID from a Twitter screen name.
 - `getRedisIdByUserId` : Generates a Redis ID from a Twitter user ID.

Key Variables:

- `SCREEN_NAME` : Twitter handle passed as a command-line argument.
- **Locale Setting:** Sets locale for number formatting.

Function: `calculate()`

1. Redis Connection:

- Connects to Redis database using default settings (localhost).

2. Fetch Follower IDs:

- Retrieves follower IDs associated with the given `SCREEN NAME` from Redis.
- Converts IDs to a list using `smembers` .

3. Fetch Follower Info:

- Uses `mget` to fetch detailed info for each follower.
- Follower data is deserialized from JSON format.

4. Frequency Calculation:

- Initializes an empty dictionary `freqs` to track followers by their **followers count** .
- For each follower, it:
 - Gets their followers count.
 - Appends the follower's details (screen name and user ID) to the appropriate count in `freqs` .

5. Data Storage:

- Saves the frequency data to Redis for future access.

6. Sorting and Output:

- Sorts keys (followers counts) and prepares to display the top 10 followers.
- Uses **PrettyTable** to format the output with columns for **User** and **Count** .
- Iterates through the top follower counts and adds their details to the table.

7. Average Calculation:

- Computes the average followers count from the collected data.

Summary

This script effectively analyzes a Twitter user's followers using Redis, allowing for efficient retrieval and display of follower statistics. It handles data storage, frequency analysis, and formatted output, making it a powerful tool for social media analysis.

Notes on Average Followers Calculation

Output of Average Followers:

- Displays the average number of followers for the specified user's followers using formatted output.
- **Key Output Example:**
 - Average followers for **SCREEN NAME** is displayed in a readable format.

Psyco Integration:

- **Psyco Module:**
 - Used to dynamically compile Python functions for performance improvements.
 - Optional, but can significantly speed up calculations that take longer than a few seconds.
- **Error Handling:**
 - If Psyco is not installed, the script will continue without it.

Function Call:

- Calls the `calculate()` function to execute the follower analysis.

Statistical Significance:

- The analysis is based on a sample size of about **150,000 followers** (approximately **10%** of Tim O'Reilly's followers).
- This large sample size ensures:
 - A **small margin of error** (~0.14 for a 99% confidence level).
 - High confidence in the representativeness of the results.

Top 10 Followers Example:

- Displays a list of the top 10 followers based on follower count:
 - **Notable Names:**
 - @aplusk (Ashton Kutcher) – 4,993,072 followers
 - Barack Obama – 4,114,901 followers
 - Other well-known figures include Martha Stewart and Arnold Schwarzenegger.

Average Followers Analysis:

- Initial average followers count: **445** .
- Removing top 10 followers lowers the average to about **284** .
- Removing followers with fewer than **10** followers significantly increases the average to over **1,000** .

Considerations:

- Many users with low follower counts may be **spam accounts** or have **protected tweets** , impacting the analysis.
- The analysis emphasizes the importance of considering user quality in follower metrics.

Summary

This script calculates the average follower count of a user's followers, leveraging Psycho for performance. It provides a statistically significant sample size, highlights notable

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Understanding Twitter Connections and Friendship Graphs

Followers Metric: Having fewer than 10 followers is a practical benchmark for evaluating Twitter users. Analyzing users with this metric can yield a significant number, around 800, which is still considerable. This highlights the potential impact of getting retweeted by influential Twitter users who have extensive networks.

Constructing Friendship Graphs

- **Data Structures:**

This chapter emphasizes using **sets** for storing and managing data, especially for collections like **ID values**. **Set operations** are efficient and require minimal effort.

- **Data Storage vs. Querying:**

There are trade-offs in how data is stored and accessed:

- **Upfront Costs:** When using specialized indexes (like **CouchDB**).
 - **Query Time Costs:** When searching without these indexes.
- Choosing a method means dealing with either **redundant storage** or the complexities of **denormalization**.

Analyzing Social Networks

- If you're exploring network topologies, consider exporting your **Redis data** to a **graph database** such as **NetworkX** (mentioned in Chapter 1).
- A common graph to analyze is the **friendship graph**, which shows connections between individuals in a social network.

Key Insights from Social Graphs: Friendship graphs offer valuable insights into social relationships. Using Twitter data, you can harvest friendship information from interesting users.

Building Friendship Graphs

Once you have friendship data in Redis, you can visualize it using NetworkX.

- **Example 4-10:** Illustrates how to create a graph of common friendships for a user.
 - This involves **nested loops** to examine all users and establish **edges** where friendships exist.

With your data in NetworkX, you gain access to a wide range of graph algorithms and tools for deeper analysis.

Example Code Overview

python Copy code

```
# -*- coding: utf-8 -*- # Summary: Create a directed graph where an edge indicates one user follows another  
import os  
import sys
```

This code snippet provides a foundational structure for building a friendship graph, setting the stage for more complex analyses in social networks.

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Building a Friendship Graph with Python

Imports and Setup:

python Copy code

```
import json  
import networkx as nx  
import redis  
from twitter_util import getRedisIdByScreenName, getRedisIdByUserId
```

- **Libraries Used:**
 - **json:** For handling JSON data.
 - **networkx (nx):** For creating and manipulating graphs.
 - **redis:** For connecting to the Redis database.
 - **twitter_util** : Custom utility functions for Twitter data retrieval.

Variables:

- **SCREEN_NAME** : Input from command line for the Twitter username.
- **g:** An instance of a **NetworkX graph** to hold the friendship data.
- **r:** Connection to the **Redis** database.

Fetching Friend IDs

1. Retrieve Friend IDs:

```
python Copy code friend_ids = list(r.smembers(getRedisIdByScreenName(SCREEN_NAME, 'friend_ids ')))
```

- This line gets all friend IDs associated with the specified **SCREEN NAME**.

2. Get User ID:

```
python Copy code id_for_screen_name = json.loads(r.get(getRedisIdByScreenName(SCREEN_NAME, 'info.json')))[ 'id' ]
```

- Retrieves and decodes the user ID for the specified screen name.

3. Compile List of IDs:

```
python Copy code ids = [id_for_screen_name] + friend_ids
```

Processing Each User

- **Iterate Through User IDs:**

```
python Copy code for current_id in ids: print >> sys.stderr, 'Processing user with id', current_id
```

 - Each user ID is processed in the loop. Errors are handled gracefully.

Fetching Friend Information

• Get Friend Information:

```
python Copy code current_info = json.loads(r.get(getRedisIdByUserId(current_id, 'info.json')))
```

- Loads data for the current user.

• Retrieve Friend IDs:

```
python Copy code friend_ids = list(r.smembers(getRedisIdByScreenName(current_screen_name, 'friend_ids ')))
```

- This retrieves the friend IDs of the current user.

• Filter Friends:

```
python Copy code friend_ids = [fid for fid in friend_ids if fid in ids]
```

- Only includes friends that are also part of the original set of IDs.

Constructing the Graph

- **Add Edges:**

```
python Copy code g.add_edge(current_screen_name, friend_info[ 'screen_name' ])
```

 - Creates a connection (edge) in the graph between the current user and their friends.

Saving the Graph

1. Check for Output Directory:

```
python Copy code if not os.path.isdir( 'out' ): os.mkdir( 'out' )
```

2. Save the Graph to Disk:

```
python Copy code filename = os.path.join( 'out' , SCREEN_NAME + '.gpickle' ) nx.write_gpickle(g, filename) print 'Pickle file stored in: %s' % filename
```

- The graph is saved as a **Pickle** file, which allows for easy loading and analysis later.

Summary

This script builds a friendship graph for a given Twitter user by leveraging Redis to retrieve user and friendship data. It processes each user, filters their friends, and constructs a graph, which is then saved for future use.

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Analyzing Friendship Graphs

Loading the Graph: To load a previously saved graph, use:

python Copy code

```
g = nx.read_gpickle( os.path.join( 'out' , SCREEN_NAME + '.gpickle' ) )
```

This command imports the graph representation of friendships stored in a Pickle file.

Clique Detection and Analysis

Clique Definition:

- A **clique** in a graph represents a group of nodes (friends) where every pair of nodes is directly connected.

Example of a Clique:

- If **Abe** is friends with **Bob** , **Carol** , and **Dale** , and **Bob** and **Carol** are also friends, the largest clique involving **Abe** , **Bob** , and **Carol** is a **maximum clique** . If all four (Abe, Bob, Carol, and Dale) are friends, the graph is fully connected, representing a clique of size 4.

Understanding Cliques:

- Adding new nodes (friends) can create more cliques but doesn't always increase the size of the maximum clique.
- **Maximum Clique:** The largest clique in the graph.
- **Maximal Clique:** A clique that cannot be extended by including one more adjacent vertex.

Key Insights:

- The maximum clique reflects the largest set of mutual friendships.
- Comparing maximum clique sizes in different social networks can reveal insights into **group dynamics**.

Illustration:

- A graph might show a maximum clique of size 4, as depicted in Figure 4-2, while also containing other maximal cliques of size 3.

Computational Complexity

- Finding cliques is classified as an **NP-complete problem**, meaning it can require exponential time to solve as the graph size increases.
- **NetworkX** offers a method called `find_cliques`, which simplifies the process of detecting cliques but can be time-consuming for larger graphs.

By analyzing cliques within a friendship graph, you can gain deeper insights into social relationships and community structures.

Analyzing Cliques in Friendship Graphs

Visual Representation:

- **Figure 4-2** illustrates a graph that contains a **maximum clique** of size 4, highlighting the importance of visualizing cliques in social networks.

Modifying Example for Analysis

Example 4-11: Finding Cliques Using NetworkX

To analyze friendship cliques in a graph, you can modify the script provided in Example 4-11. The initial step is to ensure you have collected the necessary friendship data and constructed the graph.

Code Breakdown:

python Copy code

```
# -*- coding: utf-8 -*- import sys import json import networkx as nx G = sys.argv[ 1 ] # Load the graph from command line input g = nx.read_gpickle (G) # Read the graph from a Pickle file
```

Finding Cliques:

- **Clique Detection:** python Copy code `cliques = [c for c in nx.find_cliques (g)]`
 - This line retrieves all cliques in the graph. Note that finding cliques is computationally intensive, especially for large graphs.

Statistics on Cliques:

1. Total Number of Cliques:

```
python Copy code num_cliques = len (cliques)
```

2. Sizes of Cliques:

```
python Copy code clique_sizes = [ len (c) for c in cliques]
```

3. Maximum Clique Size:

```
python Copy code max_clique_size = max (clique_sizes )
```

4. Average Clique Size:

```
python Copy code avg_clique_size = sum (clique_sizes ) / num_cliques
```

5. Identifying Maximum Cliques:

```
python Copy code max_cliques = [c for c in cliques if len (c) == max_clique_size ] num_max_cliques = len (max_cliques )
```

Summary of Analysis

This example demonstrates how to utilize NetworkX for detecting and analyzing cliques within a social network graph. By extracting statistics like the total number of cliques, maximum and average sizes, you can gain valuable insights into the structure of friendships. The analysis reveals not only the largest group of mutual friends but also the overall dynamics within the network.

Analyzing Maximum Cliques

Finding Common Members:

python Copy code

```
max_clique_sets = [set(c) for c in max_cliques] people_in_every_max_clique = list(reduce(lambda x, y: x.intersection(y), max_clique_sets))
```

- This code converts maximum cliques into sets and then identifies individuals who are present in all maximum cliques by calculating the **intersection** of these sets.

Output Summary:

python Copy code

```
print 'Num cliques:', num_cliques print 'Avg clique size:', avg_clique_size print 'Max clique size:', max_clique_size
print 'Num max cliques:', num_max_cliques print print 'People in all max cliques:' print json.dumps(people_in_every_max_clique, indent=4) print print 'Max cliques:' print json.dumps(max_cliques, indent=4)
```

- This portion of the code outputs the following statistics:
 - **Total Number of Cliques:** Total cliques found in the network.
 - **Average Clique Size:** The mean size of all cliques.
 - **Maximum Clique Size:** The size of the largest clique.
 - **Number of Maximum Cliques:** The total number of cliques that are of maximum size.

Sample Output Analysis

For Tim O'Reilly's friendship network, the analysis yielded:

- **Total Cliques: 762,573**
- **Average Clique Size: 14**
- **Maximum Clique Size: 26**
- **Number of Maximal Cliques: 6**

This indicates that the largest fully connected group among Tim's friends consists of 26 individuals, and there are 6 distinct cliques of this size. Notably, 20 out of the 26 individuals are common across all 6 cliques, suggesting they play a crucial role in Tim's social network.

Insights and Applications

Discovering cliques, particularly maximal and maximum cliques , provides significant insights into complex social data. Analyzing the similarity and diversity of tweet content among members of a large clique could offer valuable perspectives on user interactions and community dynamics. Further exploration of tweet analysis will be cov

Maximum Cliques and Analysis Opportunities

List of Members in Maximum Cliques: The maximum cliques identified include key individuals such as:

- dweinberger
- timoreilly
- ev
- jason pontin
- kevinmarks
- MIsif

Example Maximum Clique: One example of a maximum clique includes the following members:

plaintext Copy code

```
[ "timoreilly", "anildash", "cshirky", "ev", "pierre", "mkapor", "johnbattelle", "kevinmarks", "MParekh", "dsearls", "kwerb", "Joi", "LindaStone", "dweinberger", "SteveCase", "leolaporte", "steverubel", "Borthwick", "godsdog", "edyson", "dangillmor", "MIsif", "JPBarlow", "stevenbjohnson", "jayrosen nyu ", "jason pontin " ]
```

Further Analysis Opportunities

Beyond just detecting cliques, there are numerous analytical avenues to explore:

1. **Geographic Correlation:**
 - Plotting the locations of individuals in cliques on a map to see if tightly connected networks correlate with specific geographic areas.
2. **Profile and Tweet Analysis:**
 - Examining the **profile data** and **tweet content** of clique members can yield deeper insights into their interactions and relationships.

Upcoming Topics

The next chapter will focus on tweet analysis , which aligns well with these ideas. It's suggested to revisit the concept of

analyzing cliques after gaining insights from the upcoming material.

Additional Resource

Before diving into tweet analysis, the chapter will introduce an interesting Web API from Infochimps that can serve as a sanity check for the analyses performed thus far.

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Infochimps “Strong Links” API Overview

Infochimps Organization:

- Infochimps provides a vast **data catalog**, including a large archive of **historical Twitter data** and various **APIs** for data manipulation.

Strong Links API:

- The **Strong Links API** is designed to return a list of users with whom a specified user communicates most frequently.

Accessing the API:

1. **Sign Up:** Create a free account to obtain an **API key**.
2. **Make a Request:** Use a simple **GET request** to access the API via a specified URL.
3. **User ID Resolution:** The API returns **user ID values**, which need to be converted to **screen names** for practical use.

Example Script: Fetching Strong Links

Example 4-13: Using the Strong Links API

python Copy code

```
# -*- coding: utf-8 -*- import sys import urllib2 import json import redis from twitter_util import getRedisIdByUserId
SCREEN_NAME = sys.argv[ 1 ] # User whose strong links are being queried API_KEY = sys.argv[ 2 ] # API key for authentication
API_ENDPOINT = 'http://api.infochimps.com/soc/net/twstrong_links.json?screen_name'
```

```
=%s&apikey=%s' r = redis.Redis() # Connect to Redis with default settings
try: url = API_ENDPOINT % (SCREEN_NAME, API_KEY) # Format the URL with user name and API key
response = urllib2.urlopen(url) # Fetch data from the API except urllib2.URLError as e:
print 'Failed to fetch ' + url # Handle errors
raise e
strong_links = json.loads(response.read()) # Parse the JSON response
# Print strong links to the screen
print "%s's Strong Links" % (SCREEN_NAME,)
print '-' * 30
for sl in strong_links['strong_links']:
    if sl is None: continue # Skip any None values
```

Key Points from the Example:

- **User Input:** The script requires a Twitter **screen name** and an **API key** as inputs.
- **Redis Integration:** The script uses **Redis** to manage data, particularly for resolving user IDs to screen names.
- **Error Handling:** It includes error handling to manage potential issues with fetching data from the API.

Future Development:

- An upcoming **“Who Is” API** from Infochimps will facilitate resolving screen names directly from user IDs, enhancing the usability of the data returned by the Strong Links API.

This API and its integration provide a powerful tool for analyzing social connections on Twitter, particularly useful for understanding communication.

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Analyzing Strong Links Data

Code Snippet for Resolving Screen Names:

python Copy code

```
try: user_info = json.loads(r.get(getRedisIdByUserId(sl[0], 'info.json')))
    print user_info['screen_name'], sl[1]
except Exception as e:
    print >> sys.stderr, "ERROR: couldn't resolve screen name for", sl
    print >> sys.stderr, "Maybe you haven't harvested data for this person yet?"
```

- This code attempts to retrieve user information from Redis using a **user ID**. If it fails, it outputs an error message indicating that data for that user may not have been collected yet.

Key Observations from Tim's Maximum Cliques:

- Among the **20 individuals** present in all **6 of Tim's maximum cliques**, only **@kevinmarks** appears in the

results from the Strong Links API.

- This suggests that strong connections on Twitter do not always translate to frequent communication.

Connections with Retweets:

- In the next chapter, it's noted that several Twitter users whom Tim frequently retweets, such as **@ahier** , **@gnat** , **@jamesoreilly** , **@pahlkadot** , **@OReillyMedia** , and **@monkchips** , are present in the strong links list.
- Particularly, **@monkchips** is highlighted as being second on the list of strong links, demonstrating a connection between retweeting and strong communication ties.

Strong Links API Insights:

- The **Infochimps Strong Links API** does not disclose the exact calculation method for determining strong links, only stating that it relies on **actual tweet content** .
- This highlights the important lesson that being closely connected on Twitter does not necessarily mean that users engage in frequent communication.

Example Output from Strong Links API:

Sample Results:

markdown Copy code

```
timoreilly's Strong Links ----- jstan 20.115004 monkchips 11.317813 gowwiki 11.199023 ahier  
10.485066 ... kevinmarks 7.7423387 gnat 7.6349654
```

- This output displays Tim O'Reilly's strong links along with associated scores, indicating the strength of communication.

Conclusion:

The analysis illustrates the nuanced relationships within Twitter connections, emphasizing that friendship and communication do not always align directly. The availability of the Strong Links API provides a valuable resource for exploring these dynamics further.

Introduction to Ubigraph:

- **Ubigraph** is a **3D interactive graph visualization tool** that can be used to visually represent graph data.
- While visualizing a **clique** may not provide analytical insights, it serves as a good exercise to learn about graph visualization.

Installation and Usage:

- **Installation** is straightforward, and Ubigraph supports several programming languages, including **Python**.
- Windows users may need to use a **Linux-based virtual machine** as Ubigraph servers are not readily available for Windows.

Example Usage:

python Copy code

```
import sys
import json
import networkx as nx
import ubigraph

SCREEN_NAME = sys.argv[1]
FRIEND = sys.argv[2]

g = nx.read_gpickle(SCREEN_NAME + '.gpickle')
cliques = [c for c in nx.find_cliques(g) if FRIEND in c]
max_clique_size = max([len(c) for c in cliques])
max_cliques = [c for c in cliques if len(c) == max_clique_size]

print('Found %s max cliques' % len(max_cliques))
print(json.dumps(max_cliques, indent=4))

U = ubigraph.Ubigraph()
U.clear()

small = U.newVertexStyle(shape='sphere', color='ffff00', size='0.2')
largeRed = U.newVertexStyle(shape='sphere', color='ff0000', size='1.0')

vertices = list(set([v for c in max_cliques for v in c]))
vertices = dict([(v, U.newVertex(style=small, label=v)) for v in vertices if v not in (SCREEN_NAME, FRIEND)])
vertices[SCREEN_NAME] = U.newVertex(style=largeRed, label=SCREEN_NAME)
vertices[FRIEND] = U.newVertex(style=largeRed, label=FRIEND)

for v1 in vertices:
```

Key Steps in the Code:

1. **Read Graph Data:** The script reads the graph data from a pickled file (`.gpickle`).
2. **Find Cliques:** It identifies all cliques containing the specified **FRIEND** and determines the maximum cliques.
3. **Visual Representation:**
 - Clears previous visualizations in Ubigraph.
 - Defines two vertex styles: **small** (for regular members) and **largeRed** (for the screen name and friend).
 - Extracts unique vertices from the maximum cliques for visualization.

Conclusion

Using Ubigraph allows for an engaging way to visualize social network graphs. While this tool may require some setup, it can effectively showcase complex rela

Building and Visualizing Graphs with Ubigraph

Creating Edges in Ubigraph:

- In the visualization process, you can connect nodes by iterating through pairs of vertices:

python Copy code

```
for v2 in vertices: if v1 == v2: continue U.newEdge(vertices[v1], vertices[v2])
```

- This creates **edges** between different **vertices** (nodes).

Key Points:

- Unlike **NetworkX**, Ubigraph does not define nodes by their labels. This means you need to ensure that you do not add duplicate nodes to the graph.
- The example illustrates how to build a graph by iterating through a **dictionary of vertices**, applying visual distinctions for better clarity.

Visualization Purpose:

- The example is designed to visualize the common members of **maximum cliques** shared between a specific user (e.g., **Tim O'Reilly**) and a defined friend (specified by **FRIEND**). This visualizes the largest clique that includes both nodes.

Summary of the Chapter:

- This chapter provides an introduction to using Twitter data, focusing on friend and follower relationships.
- A sample command-line tool implementing the functionalities discussed is available on GitHub, encouraging users to adapt it for their needs.

Suggested Exercises:

1. Geo Data Exploration:

- Analyze the geographic locations of your followers by plotting a histogram and visualizing it on an online map. Chapter 6 offers insights into mapping technologies.

2. Frequency Analysis:

- Conduct a basic frequency analysis of the words in the description fields of user objects for your friends and followers. Chapters 7 and 8 provide helpful tools for this.

3. Tweet Frequency Histogram:

- Create a histogram showing the number of tweets from each follower to identify the most active users. This information is available as `statuses_count` in user objects.

4. List Analysis:

- Investigate Twitter **lists** , which group users with common themes. Use the API to check who has listed you or other Twitter users you admire, and explore the similarities among users in those lists.

This chapter serves as a starting point for deeper analysis of Twitter data, inviting further exploration and experimentation.

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Interactive 3D Visualization of Maximal Cliques

Figure 4-3 Overview:

- The figure showcases a **3D interactive visualization** highlighting common members in the **maximal cliques** that include both **@timoreilly** and **@mikeloukides** .
- The screenshot provides a glimpse into the visualization, but experiencing it interactively offers a much richer understanding.

Key Points:

- **Maximal Cliques** : These are groups of users who are mutually connected, showcasing the network's tightly-knit relationships.
- **Interactive Experience** : Engaging with the visualization tool allows users to explore the data dynamically, enhancing the analysis of social connections.

Conclusion

- Visualizations like this help to better understand complex social networks, revealing the structure and relationships among users. Exploring such tools can significantly deepen insights into Twitter interactions.

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Chapter 5: Twitter - Analyzing Tweets

Introduction:

- This chapter focuses on using **CouchDB's map/reduce** capabilities to analyze the content of tweets, including **@mentions** , **#hashtags** , and other entities.
- The goal is to explore the question: **"What's everyone talking about?"**
- With over **50 million tweets** daily and peaks of **3,000 tweets per second** , there's significant potential for **mining tweet content** .

Key Concepts:

- Previous chapters (especially **Chapters 3 and 4**) set the foundation, introducing tools like **Redis** and **CouchDB** that will be utilized here.
- While the last chapter dealt with **social graph linkages** (connections between users), this chapter shifts the focus to the content of tweets and what can be learned about Twitter users from them.

The Power of Tweets:

- The chapter humorously compares the significance of tweets to weapons, suggesting that if **the pen is mightier than the sword** , then a tweet could be likened to a **machine gun** .
- It references real-life incidents where tweets have had profound impacts, such as:
 - **James Karl Buck's "Arrested" tweet** , which facilitated his release from detention in Egypt.
 - Numerous instances of Twitter being used for **fundraising** and **benevolent causes** .

Conclusion:

- The chapter emphasizes the power of tweets as a communication tool and the potential insights that can be gained from analyzing their content. Readers are encouraged to dive into this analysis to uncover the rich narratives within Twitter data.

Analyzing Tweet Content

Overview:

- While many tweets on the **public timeline** may lack excitement, analyzing the **entities** within tweets can reveal valuable insights.
- About **50% of tweets** include at least one entity that the author intentionally included, making them an excellent starting point for analysis.

Importance of Tweet Entities:

- Twitter acknowledges the significance of entities and has made them accessible through the **timeline API** calls.
- By early 2010, including entities in API responses became a standard practice.

Example Tweet Analysis (Example 5-1):

- A sample tweet retrieved using the **include entities =true** parameter shows how entities are structured:

json Copy code

```
{ "created_at": "Thu Jun 24 14:21:11 +0000 2010", "entities": { "hashtags": [ { "indices": [ 97, 103 ], "text": "gov20" }, { "indices": [ 104, 112 ], "text": "opengov" } ], "urls": [ { "expanded_url": null, "indices": [ 76, 96 ], "url": "http://bit.ly/9o4uoG" } ], "user_mentions": [ { "id": 28165790, "indices": [ 16, 28 ], "name": "crowdFlower", "screen_name": "@crowdFlower" } ] }, "id": 16932571217, "text": "Great idea from @crowdflower: Crowdsourcing the Goldman ... #opengov", "user": { "description": "Founder and CEO, O'Reilly Media. Watching the alpha ...", "id": 2384071, "location": "Sebastopol, CA", "name": "Tim O'Reilly", "screen_name": "timoreilly", "url": "http://radar.oreilly.com" } }
```

Key Insights from the Sample Tweet:

- The **user field** provides information about the author, while the **entities** field gives context to the tweet's content.
- In the example, we see:
 - **Hashtags** : #gov20 and #opengov indicate topics being discussed.
 - **User Mentions** : The tweet references @crowdflower , showing engagement with another user.
 - **URLs** : Links to additional content, enriching the tweet's context.

Conclusion:

- By analyzing the entities within tweets, we can better understand the themes and discussions occurring on Twitter, moving beyond superficial content to grasp deeper meanings and connections.

Overview:

- In a tweet by **@timoreilly** , the inclusion of hashtags like **#gov20** and **#opengov** suggests an interest in **open government** and **Government 2.0** topics.
- The mention of **@crowdfunder** indicates a potential connection to these themes, and the URL likely leads to relevant content.

Exploring Related Information:

- To gather more context about **@timoreilly** or **@crowdfunder** , you could:
 - **Examine** @crowdfunder's tweets and profile.
 - **Search** for other tweets using the same hashtags to uncover related discussions.
 - **Follow the link** in the tweet for additional insights, possibly using **web scraping** techniques.

Value of Tweet Entities:

- Analyzing tweet entities can yield significant insights, but they may be missing in some APIs or historical Twitter data archives.
- Instead of manually parsing entities from tweet text (which can be complex due to **Unicode characters**), use the **twitter-text-py** library for easier extraction.

Using the Twitter Text Package (Example 5-2):

- The following script demonstrates how to extract tweet entities using the **twitter_text** package:

python Copy code

```
# -*- coding: utf-8 -*- import sys import json import twitter_text import twitter from twitter import _login import login # Get a tweet ID by clicking on a status on twitter.com TWEET_ID = sys.argv[ 1 ]
```

Current State of Tweet Entities:

- As of December 2010, tweet entities were becoming more common in APIs but were not yet standardized.
- Understanding how to manually extract tweet entities can be beneficial, especially when working with **historical data** from sources like **Infochimps** or **GNIP** .

Conclusion:

- Utilizing automated tools to extract tweet entities will enhance your analysis, allowing you to focus on more interesting problems and insights, rather than manual parsing. Staying updated with Twitter API changes can further st

Extracting Tweet Entities and Analyzing Tweets

OAuth Setup:

- Ensure your **OAuth settings** are configured in the `twitter_login.py` file to authenticate API calls.

Extracting Entities from Tweets:

- The function `getEntities(tweet)` extracts various entities from a tweet's text and organizes them into a structured format:
 - **User Mentions** : The function uses `twitter_text.Extractor` to identify mentioned users.
 - **Hashtags** : Extracted hashtags are modified to match the Twitter API format by changing the field name from `hashtag` to `text`.
 - **URLs** : URLs from the tweet are extracted and stored in a list.

Code Implementation:

python Copy code

```
t = login() # Authenticate using OAuth
def getEntities ( tweet ):
    extractor = twitter_text.Extractor(tweet['text']) # Create an extractor for the tweet's text
    entities = { 'user_mentions' : [um for um in extractor.extract_mentions_screen_names_with_indices ()],
                'hashtags' : [{ 'text' : ht['hashtag'] } for ht in extractor.extract_hashtags_with_indices ()],
                'urls' : [url for url in extractor.extract_urls_with_indices ()] }
    return entities # Fetch the tweet using an API method
tweet = t.statuses.show( id=TWEET_ID )
tweet['entities'] = getEntities(tweet) # Add extracted entities to the tweet
print (json.dumps(tweet, indent=4)) # Print the tweet with entities in a readable format
```

Advantages of Using CouchDB for Tweet Storage:

- **CouchDB** is an excellent choice for storing tweets due to:
 - Its ability to represent data as **JSON documents**.
 - Compatibility with **map/reduce analysis**, making it easy to process and analyze large volumes of tweets.

Next Steps:

- With the ability to extract and analyze tweet entities established, you can now proceed to harvest and analyze tweets in a structured way. This lays the foundation for deeper insights into Twitter data.

Harvesting Tweets with CouchDB

Overview:

- This section discusses how to harvest tweets efficiently using **CouchDB** and the **Twitter API**.
- The process incorporates a **map/reduce job** to track the maximum tweet ID, preventing duplicates when fetching data.

Key Parameters:

- **since_id** : This parameter helps avoid duplicate data by querying tweets with IDs greater than the specified maximum.
- **Tweet Limits** :
 - Up to **3,200 recent tweets** can be retrieved from a user timeline.
 - The **home timeline** provides about **800 statuses**.
 - The **public timeline** returns only **20 tweets**, updated every **60 seconds**.

Streaming API:

- For larger data collections, consider using the **streaming API** instead of standard timeline requests.

Example Usage:

- To gather tweets from a specific user, like **Tim O'Reilly**, run the following command: `bash Copy code $ python the_tweet_harvest_timeline.py user 16 timoreilly`
- This command initiates the script to collect around **3,200 tweets** for analysis.

Script Breakdown (Example 5-3):

- The script `the_tweet_harvest_timeline.py` facilitates the harvesting process, using the following key components:
 - **Imports** necessary libraries, including `twitter`, `couchdb`, and custom utility functions.
 - Defines a **usage function** that explains command-line parameters for the script:
 - `timeline_name` : Options include **public**, **home**, or **user** timelines.
 - `max_pages` : Limits for pages of data (up to 16 for home/user, only 1 for public).

Notes:

- Be aware of the limitations on the number of statuses that can be retrieved from different timelines.
- For in-depth data analysis, leverage additional features provided by the **streaming/search API**.

This setup allows for a comprehensive exploration of Twitter data, facilitating richer analyses and insights.

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Handling Twitter Timeline Data Collection

Input Validation:

- The script starts by checking the command-line arguments:
 - If fewer than **2 arguments** are provided or the first argument isn't one of **public**, **home**, or **user**, it calls the **usage()** function.
 - If the second argument exists but isn't a digit, or if there are more than **3 arguments** when the first is **user**, it also calls **usage()**.

Key Variables:

- **TIMELINE NAME** : Set from the first argument (`public`, `home`, or `user`).
- **MAX PAGES** : Maximum number of pages to fetch, set from the second argument (default 200 tweets per page).
- **USER** : Initialized as `None`. If the timeline is **user**, it takes the third argument as the user's ID or screen name.

Limits on Pages:

- The script enforces maximum page limits based on the timeline type:
 - For **home** timelines, **MAX PAGES** is capped at **4**.
 - For **user** timelines, it's capped at **16**.
 - For **public** timelines, it's restricted to **1**.

Twitter API Parameters:

- A dictionary **KW** is prepared for the Twitter API call with:
 - `'count'` : Number of tweets to fetch per request (200).
 - `'skip_users'` : Avoid fetching user data.
 - `'include_entities'` : Include metadata about tweet entities.
 - `'since_id'` : Starts from the tweet with ID 1.

Database Setup:

- **CouchDB Connection** : Establishes a connection to a local CouchDB server.
- **DB Name** : Creates a database name based on the timeline type, appending the user if applicable.

Database Creation:

- The script attempts to create the database:
 - If it already exists (indicated by a **PreconditionFailed** error), it connects to the existing database.
 - The script implements a **mapper/reducer** function to identify the maximum tweet ID already in the database. This helps avoid duplicate tweets for **home** and **user** timelines. For the **public** timeline, this check is not applicable.

This process sets up the script to

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Collecting and Analyzing Tweets

Tweet ID Mapper and Reducer:

- **idMapper(doc)** : A function that yields the tweet ID from each document (tweet).
- **maxFindingReducer(keys, values, rereduce)** : A reducer function that returns the maximum value from the list of tweet IDs.
- **viewDefinition** : Creates a view called **max tweet_id** to find the maximum tweet ID in the CouchDB database, using the above mapper and reducer functions. It is synchronized with the database.

Fetching the Latest Tweet ID:

- The script retrieves the latest tweet ID from the view created, storing it in **KW['since_id']**. This helps avoid fetching duplicate tweets.

Tweet Harvesting Process:

- The maximum number of tweets is generally around **800** for friend and home timelines. For the public timeline, only **20** tweets are returned and updated every **60 seconds**.
- The **count** and **since_id** parameters do not impact the public timeline's results.

Tweet Retrieval Loop:

- The script enters a loop, running up to **MAX PAGES** :
 - `kw['page']` is updated to track the current page of tweets.
 - The appropriate API call is determined based on the **TIMELINE NAME** (public, home, or user).
 - Tweets are fetched using **makeTwitterRequest** and stored in the CouchDB database.
 - The script prints the number of tweets fetched and pauses for **2 seconds** before fetching the next page.

Analyzing Tim O'Reilly's Tweets

The following questions will guide the analysis of tweets collected from Tim O'Reilly's timeline:

1. **Friendship Analysis** : How many frequently mentioned entities in Tim's tweets are his friends?
2. **Entity Frequency** : What are the most common entities found in Tim's tweets?
3. **Retweet Analysis** : Who does Tim retweet the most?
4. **Retweet Count** : How many of Tim's tweets have been retweeted?

This framework sets up a structured way to explore and analyze tweets, using both the collected data and relevant qu

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It looks like you might have sent an incomplete message. How can I assist you further?

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Here's a simplified and detailed restatement of the provided content:

Extracting and Analyzing Tweet Entities

Key Process: Extracting Entities from Tweets

- **Entity Extraction** : The `twitter_text.Extractor` is used to analyze the text of a tweet.
- **Entities Identified** : The main entities extracted are:
 - **User Mentions** : Screen names of users mentioned in the tweet.
 - **Hashtags** : Keywords preceded by a "#" symbol.
 - **URLs** : Links included in the tweet.

Structure for Storing Entities

- An `entities` dictionary is created to store these extracted entities:
 - **user mentions** : List of mentioned users.
 - **hashtags** : List of hashtags, with the field name modified for compatibility.
 - **urls** : List of URLs.

Entity Mapping for Database Storage

- The function iterates through the entities to yield results for database indexing:
 - For **User Mentions** : Yields pairs of the screen name and corresponding tweet IDs.
 - For **Hashtags** : Yields pairs of hashtags and tweet IDs.
 - For **URLs** : Yields pairs of URLs and tweet IDs.

Reducer Function for Counting

- The `summingReducer` function counts the occurrences of entities:
 - If it's a re-reduce operation, it sums the values.
 - Otherwise, it returns the count of unique values.

Database View Definition

- A **view** called `entity_count_by_doc` is created to count entities per document (tweet):
 - **Mapper** : Uses `entityCountMapper` to categorize entities.
 - **Reducer** : Uses `summingReducer` to calculate total counts.
- This view is synchronized with the CouchDB database.

Output and Sorting

- The entities are sorted and displayed in a table format:
 - The results are grouped and sorted by the entity cou

Here's a clearer and more concise restatement of the provided content:

Displaying and Analyzing Entity Frequencies

Creating a Frequency Table

- A frequency table is built using **PrettyTable** to display entities and their counts.
- The **fields** are defined as `['Entity', 'Count']`.
- The table aligns the fields to the left for readability.

Populating the Table

- The script iterates through `entities_freqs`, which contains entity-frequency pairs.
- It adds a row to the table only if the frequency exceeds a predefined **FREQ_THRESHOLD**.

Printing the Table

- Finally, the table is printed to show the results clearly.

Importance of the rereduce Parameter

Understanding rereduce

- The example highlights the significance of the **rereduce** parameter in map/reduce jobs.
- **Initial reduction** groups data from multiple mappers, while **rereduce** applies to output from reducers.

Functionality of summingReducer

- The `summingReducer` can handle different inputs based on whether it is the first reduction or a rereduction.
- For counting or summing operations, it doesn't matter where the input comes from, as long as a commutative operation (like addition) is used.

Example Input for the Reducer

- During the initial pass (when `rereduce` is false), the reducer processes grouped values:
 - For example, `summingReducer` would handle multiple entries for `@foo` and `@bar`, counting occurrences.
- On the next pass (when `rereduce` is true), it operates on already reduced values, which are further grouped by key.

This summary captures the essence of displaying frequency counts and the role o

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Here's a clearer and more concise restatement of the provided content:

Understanding the rereduce Process in Tweet Analysis

Role of rereduce

- The **rereduce** phase is crucial for calculating final tallies of tweet entities after initial counting.
- In this phase, the **summingReducer** takes intermediate counts and sums them to produce a final value.

Example of Summing Values

- For instance, if the counts for @foo are [2, 1], the rereduce operation would sum these values:
 - `summingReducer(None, [2, 1], True)` results in 3 .
- Similarly, for @bar , with counts [2] , the sum is simply 2 :
 - `summingReducer(None, [2], True)` results in 2 .

Process Overview

- Initially, the **len** function counts occurrences of each entity (like a tweet mention).
- This count serves as an intermediate step before the rereduction, where totals are calculated.

Mapping and Reducing Entities

Mapping Phase

- The script uses a **mapper** to create tuples in the format `(entity, [couchdb_id , tweet_id])` for each tweet.

Reducing Phase

- The **reducer** then counts how many times each unique entity appears across all tweets.

Sorting and Thresholding

- After collecting the data, it can be sorted on the client side since the dataset is manageable.
- A **frequency threshold** is applied to filter results, focusing on the most relevant entities.

Example Output

- An example of entities sorted by frequency from tweets by **@timoreilly** shows the following (with a threshold of 15):

Entity	Frequency
#gov20	140
@OReillyMedia	124
#Ebook	89
@timoreilly	77
#ebooks	55
@slashdot	45
@jamesoreilly	41
#w2e	40
@gnat	38
@n2vip	37
@monkchips	33
#w2s	31
@pahlkadot	30
@dalepd	28
#g2e	

Frequency of Entities Retweeted by @timoreilly

This table lists entities that have been retweeted by @timoreilly along with their respective frequencies:

Entity	Frequency
@ahier	24
#where20	22
@digiphile	21
@fredwilson	20
@brady	19

Entity	Frequency
@mikeloukides	19
#pdf10	19
@nytimes	18
#fooeast	18
@andrewsavikas	17
@CodeforAmerica	16
@make	16
@pkedrosky	16
@carlmalamud	15
#make	15
#opengov	15

Key Insights

- **Popular Mentions** : The entities include both **user mentions** (like @ahier, @fredwilson) and **hashtags** (#where20, #opengov).
- **High Engagement** : Frequencies range from 15 to 24, indicating these entities are significantly engaged with by @timoreilly in recent tweets.

This data helps analyze the trends and interests reflected in @timoreilly's retweets, showcasing influential users and relevant topics in the Tw

Analyzing Tim O'Reilly's Recent Topics

Tim O'Reilly's recent tweet activity reveals several key topics and relationships. Here are the main insights:

1. **Dominant Topics** :
 - The hashtag **#gov20** stands out with **140 mentions** , significantly more than other topics, indicating its importance in Tim's discussions.
2. **User Mentions** :
 - Frequent mentions of certain users suggest **close relationships** or influence. These users may be those Tim respects or trusts, which can be analyzed further through algorithms designed to measure these connections.
3. **Time-Based Filtering** :
 - While analyzing raw counts is informative, applying a **time-based filter** could enhance insights. For instance, examining Tim's tweets over the past few days could show trending topics, rather than looking at all 3,200 tweets which span a longer time frame.
4. **Visualizing Data** :

- Tools like the **SIMILE Timeline** can help visualize Tim's tweet patterns over time, providing a clearer understanding of his recent interests.

Examining User Relationships

To explore whether frequently mentioned users are also Tim's friends:

- **Previous Data** : The earlier example (Example 4-4) explains how to gather Tim's friends and followers, which can be stored in **Redis** .
- **Comparison Process** :
 - You can compare the frequently mentioned user entities against Tim's friends in Redis using in-memory operations.
 - This involves resolving user screen names from user IDs and checking how many of the most mentioned users are Tim's friends.

Example Script Overview

- The script (Example 5-5) named **the_tweet_how_many_user_entities_are_friends.py** accomplishes this task:
 - It connects to Redis.
 - It computes screen names for Tim's friends and compares them with frequently mentioned users.

These insights provide a deeper understanding of Tim O'Reilly's online interactions and interests, which could be valuable

Identifying Friends Among Mentioned Users in Tweets

This section explains how to determine which users Tim O'Reilly frequently mentions in his tweets are also his friends.

1. Gathering Friend IDs :

- The script retrieves **friend IDs** from Redis using the screen name provided.
- These IDs are stored in a set called **friend_ids** .

2. Fetching Friend Screen Names :

- For each **friend ID** , the script attempts to get the corresponding screen name.
- If the data is not available in Redis, it skips that ID.

3. Accessing Tweet Entities :

- The script connects to a **CouchDB** database where Tim's tweet data is stored.

- It retrieves a list of **(entity, frequency)** tuples, sorted by frequency.

4. Filtering User Entities :

- It filters the entities to keep only user mentions (those starting with @) that meet a defined **frequency threshold** (e.g., 15 mentions).

5. Set Comparisons :

- The script performs set operations to identify:
 - **Entities who are friends** : Users mentioned in tweets who are also in the friends list.
 - **Entities who are not friends** : Users mentioned in tweets who are not friends.

6. Output Results :

- The script prints:
 - Total number of user entities mentioned in tweets.
 - Count of user entities who are friends.
 - Names of friends mentioned.
 - Count of user entities who are not friends.
 - Names of non-friends mentioned.

Sample Output

- With a frequency threshold of 15:
 - **Total user entities** : 20
 - **Friends among mentioned entities** : 18
 - Example friends listed: ahier , pkedrosky , CodeforAmerica , nytimes , brady .

This process helps illustrate the relationship dynamics between Tim O'Reilly and the users he frequently mentions in h

Here's a clearer and more concise restatement of the content, organized for better readability while retaining detail:

Key User Entities in Tweets

The following users are frequently mentioned in the context of tweets:

- carlmalamud
- pahlkadot
- make
- jamesoreilly
- andrewsavikas
- gnat
- slashdot
- OReillyMedia
- dalepd

- mikeloukides
- monkchips
- fredwilson
- digiphile

Summary of User Relationships

- **Total User Entities** : 20 user entities exceeded a frequency threshold of 15 mentions.
- **Friendship Analysis** : Among these, 18 are confirmed friends. This suggests a **strong trust relationship** between Tim O'Reilly and these individuals.
- **Notable Mentions** :
 - Tim himself is frequently tweeted about, along with **@n2vip** .
 - There are only **2 users** in the tweets who are not friends: **@n2vip** and **@timoreilly** .

Insights on Mentions

- The high frequency of mentions raises questions about how **non-friend users** like **@n2vip** appear in tweets. This warrants further exploration.
- Comparing this list with previous exercises on constructing **friendship graphs** can yield interesting insights.

Querying Tweets with CouchDB and Lucene

To analyze tweets mentioning **@n2vip**, we can utilize Lucene's full-text indexing capabilities in a CouchDB database. Below is an example of how to set this up:

Example 5-7: Querying Tweet Data

python Copy code

```
# -*- coding: utf-8 -*- import sys import httplib from urllib import quote import json import couchdb DB = sys.argv[ 1 ] #
CouchDB database name QUERY = sys.argv[ 2 ] # Search query # JavaScript-based design document for indexing
dd = \{ 'fulltext' : { 'by_text' : { 'index' : '''function(doc) { var ret=newDocument(); ret.add(doc.text);
```

Key Takeaways

- **Data Retrieval** : Using Lucene with CouchDB allows for efficient querying of tweet data based on text.
- **Analysis Opportunities** : The context of tweets involving **@n2vip** could provide valuable insights into online interactions and relationships.

By utilizing these tools and insights, further analysis of social media interactions can be conducted, enhancing our understanding of user dynamics and engagement.

Setting Up and Querying CouchDB with Lucene

1. Connecting to CouchDB :

- The script starts by connecting to a **CouchDB server** running locally at `http://localhost:5984` .
- It attempts to access a specified database (`DB`). If the database is not found, an error message is displayed and the script exits.

2. Checking for a Design Document :

- The script checks if a specific **design document** named `design /lucene` exists within the database.
- If it does not exist (response status 404), the script creates this design document using a JSON representation (`dd`).

3. Creating the Design Document :

- The design document allows for **full-text indexing** capabilities using Lucene.
- It can be created via a PUT request, similar to executing a command in a terminal.

4. Querying with Lucene :

- Once the design document is confirmed to exist, the script queries the database using CouchDB-Lucene's **full-text index** (FTI) handler.
- The query is formed to search for a specific term (`QUERY`), allowing for efficient text-based searches.

5. Handling API Responses :

- After sending the query, the response is checked. If successful (status 200), the results are processed and parsed into a JSON format.
- If an error occurs, a message is printed, and it prompts the user to ensure that the CouchDB-Lucene server is operational.

6. Extracting Document IDs :

- The document IDs from the response are collected, which can be used later for retrieving specific tweets or data entries.

Summary

This script outlines how to set up and use CouchDB with Lucene for effective data indexing and querying. By ensuring the design document is in place and utilizing full-text search capabilities, it enhances the ability to retrieve relevant information from the database efficiently.

1. Extracting Tweets :

- The script retrieves tweets from CouchDB using document IDs collected earlier. It specifically extracts the **text** of each tweet for display.
- This is achieved with a list comprehension: `tweets = [db.get(doc_id)['text'] for doc_id in doc_ids]`.

2. Displaying Tweets :

- Each tweet is printed to the console, separated by a blank line for clarity.

Engagement Between Users

• Conversations Highlighted :

- The output illustrates that **@n2vip** frequently appears in **@timoreilly's tweets** due to their ongoing Twitter conversations.
- This suggests a dynamic interaction between the two users, indicating a strong conversational thread.

Sample Output Analysis (Example 5-8)

- The sample output shows various tweets where **@n2vip** is mentioned. These include:
 - Discussions about eBooks and recommendations.
 - Political commentary, evidenced by mentions of health care reform and renewable energy.
 - Engaging with current events and societal issues.

Understanding the Context

• Nature of Discussions :

- The interactions appear to be somewhat **political**, supported by the presence of the **#gov20** hashtag in previous discussions.
- This context suggests that **@timoreilly** and **@n2vip** are not only friends but also share interests in various topical discussions.

Future Analysis

• Reassembling Conversations :

- A potential next step is to modify the script to extract **in_reply_to_status_id** fields from the tweets. This would allow for a more complete reconstruction of the conversations.
- Such an analysis could provide deeper insights into the interactions and topics that engage these users.

Conclusion

This process of retrieving and analyzing tweets from CouchDB illustrates how users engage in meaningful discussions on Twitter. By understanding the context and content of these interactions, we can better comprehend the dynamics of online conversations.

Reconstructing Twitter Discussion Threads

1. Minimizing API Calls :

- To efficiently reconstruct a discussion thread, instead of retrieving each tweet individually, fetch all of **@n2vip's** tweets that have tweet IDs greater than the minimum ID of interest. This method reduces the number of API calls.

2. Example Script :

- Example 5-9 demonstrates how to implement this technique in Python (the `tweet__reassemble_discussion_thread.py`):

```
python Copy code # -*- coding: utf-8 -*- import sys import httplib from urllib import quote import
json import couchdb from twitter_login import login from twitter_util import
makeTwitterRequest DB = sys.argv[ 1 ] # CouchDB database name USER = sys.argv[ 2 ] # User to query
# Connect to CouchDB try : server = couchdb.Server( 'http://localhost:5984' ) db = server[DB]
except couchdb.http.ResourceNotFound: print >> sys.stderr, ""CouchDB database '%s' not found.
Please check that the database exists and try again."" % DB sys.exit( 1 ) # Query tweets by user
try : conn = httplib.HTTPConnection( 'localhost' , 5984 ) conn.request( 'GET' , '/%s/ fti /
design /lucene/by text ?q=%s' % (DB, quote(USER))) response = conn.getresponse() if
response.status == 200 : response_body = json.loads(response.read()) else : print >>
sys.stderr, 'An error occurred fetching the response: %s %s' % (response.status, response.reason)
sys.exit( 1 ) finally : conn.close() # Extract document IDs doc_ids = [row[ 'id' ] for row in
response_body [ 'rows' ]] # Retrieve tweets from CouchDB tweets = [db.get(doc_id) for doc_id
in doc_ids ]
```

3. Extracting Conversation Threads :

- The script collects tweets and identifies the `in_reply_to_status_id` fields. This allows you to understand which tweets are replies and helps in organizing the discussion.

4. Sorting Conversations :

- The tweets are sorted based on their reply IDs to structure the conversation flow, making it easier to analyze the interactions.

Summary

This method outlines an effective way to reconstruct Twitter discussion threads by fetching tweets in bulk based on their IDs. This approach minimizes API calls and helps in organizing conversations for better analysis.

Analyzing Twitter Conversations

1. Filtering Tweets :

- The code filters tweets to identify those with a valid `in reply_to_status_id` , indicating they are replies to other tweets. This is essential for reconstructing conversation threads.

2. Finding Conversation Boundaries :

- `min conversation_id` and `max conversation_id` are calculated to define the range of tweets in the conversation. These represent the smallest and largest tweet IDs from the collected replies.

3. Fetching Reply Tweets :

- The script uses the **user timeline API** to gather tweets from a specific user, aiming to reduce API costs by pulling multiple tweets at once:

```
python Copy code results = makeTwitterRequest(t, t.statuses.user_timeline , count= 200 , since
id =min conversation_id , max id =max conversation_id , skip_users = 'true' , screen
name =USER, page=page)
```

4. Handling API Responses :

- The script iteratively requests tweets in pages until no more results are returned. This approach ensures all relevant tweets are fetched efficiently.

5. Dealing with Missing Tweets :

- A workaround is implemented for cases where tweets may not be retrieved or return null IDs. If a reply tweet is missing, the script attempts to **refetch** it individually.

6. Displaying Tweets :

- The tweets are printed out, showing the flow of conversation. For each reply tweet, if found, its text is displayed alongside the original tweet stored in the database.

7. Code Efficiency :

- This process showcases how to leverage Twitter's API effectively while minimizing logic complexity. By integrating local data storage and remote data fetching, the script maximizes functionality with streamlined code.

Summary

This approach enables a detailed analysis of Twitter conversations by efficiently retrieving and reconstructing threads. By focusing on replies and utilizing the user timeline API, it enhances the understanding of interactions between users like @timoreilly and @n2vip .

Key Notes on Retweet Analysis

Context : This section discusses analyzing retweets by a user named Tim, focusing on who he retweets most often.

Retweet Definition : A retweet indicates approval or interest in another user's content. There are two main formats:

- **RT @user** : Directly credits the user.
- **(via @user)** : Mentions the user without direct formatting.

Analysis of Tim's Retweets

1. **Purpose** : Understanding who Tim finds valuable in the Twitter community by examining his retweet patterns.
2. **Research Hypothesis** :
 - The users Tim retweets are likely those he considers influential or relevant.
 - By analyzing a sample of Tim's tweets, we can identify patterns and notable users.
3. **Data Collection** :
 - Utilize existing tweets for analysis rather than fetching new data.
 - Apply **API methods** for efficient data extraction.
4. **Retweet Patterns** :
 - Analyze retweet frequency to determine the most cited users.
 - Use a **regular expression matcher** in a map/reduce routine to extract retweet data.
5. **Significance** :
 - Retweets serve as a metric of appreciation and engagement within the Twitter ecosystem.
 - Identifying frequently retweeted users can provide insights into current trends and important discussions.

Conclusion

Analyzing Tim's retweet behavior offers valuable insights into his preferences and the broader Twitter landscape. This methodology can be applied to assess engagement and influence within social media networks.

Notes on Twitter API Retweet Analysis

Overview : The Twitter API is rapidly evolving, and there are more efficient methods for counting retweets. The following code example shows how to count the number of times users have been retweeted.

Key Concepts

1. Retweet Counting :

- Retweets are identified by keywords like "RT" and "via" in the tweet text.
- This method may become outdated as the API improves.

2. Example Code : `the_tweet__count_retweets_of_other_users.py`

Code Breakdown :

- **Imports :**
 - `couchdb` : For database interaction.
 - `prettytable` : For displaying results neatly.
- **Database Connection :**
 - Connects to a CouchDB instance to access tweets.
 - Handles errors if the database is not found.
- **Frequency Threshold :**
 - Default threshold for counting is set to 3 if not specified.

3. Functions :

- **entityCountMapper(doc) :**
 - Processes each tweet document.
 - Uses **regular expressions** to find retweet patterns.
 - Yields user mentions and their associated document IDs.
- **summingReducer(keys, values, rereduce) :**
 - Summarizes counts of retweets.
 - Returns total counts based on whether it's a re-reduce operation.

4. View Definition :

- Creates a view for counting retweets based on user mentions.

Conclusion

This method effectively counts retweets from tweet data using CouchDB, but users should be aware of potential advancements in the Twitter API that may streamline this process further.

Notes on Retweet Analysis and Results

Overview : This section discusses counting and normalizing retweets, providing insights into user interactions on Twitter.

Key Concepts

1. Data Sorting :

- **Sorting by Value :** Efficiently sorts retweet counts using Python's built-in functions.
- This is manageable for datasets with hundreds or low thousands of tweets.

2. Code Breakdown :

- **Entities Frequency Calculation** : python Copy code

```
entities_freqs = sorted([(row.key, row.value) for row in db.view('index/retweet_entity_count_by_doc', group=True)], key=lambda x: x[1], reverse=True)
```
- **Display Setup** :
 - Uses `PrettyTable` to create a formatted table for results.
 - Aligns columns for better readability.
- **Threshold Filtering** :
 - Only includes entities with counts above a specified threshold (`FREQ_THRESHOLD`).

3. Results Presentation :

- **Table Example** : Displays retweet data including:
 - **Entity** : User mentioned.
 - **Count** : Number of times retweeted.
 - **Total Tweets** : Overall tweets by the user.
 - **Normalized Retweet Score** : Indicates engagement relative to total tweets.
- Example from Table 5-2 includes several users and their retweet metrics.

4. Observations :

- Tim's retweets primarily feature users closely associated with his company, such as **@oreillymedia**.
- **Correlation** : Higher retweet counts align with higher total tweet counts for these users.
- **Normalization Insight** : While raw counts are informative, normalizing provides a clearer picture of engagement, revealing different relationships between users.

Conclusion

Analyzing retweet counts with normalization reveals deeper insights into user interactions and preferences on Twitter. Tim's retweet patterns reflect strong ties to his professional network, particularly his company.

Notes on Retweet Analysis and Influence Measurement

Overview : This section discusses the comparison of retweet frequencies among users and the measurement of influence based on retweet activity.

Key Concepts

1. Normalized Retweet Ranking :

- **Comparison of @dalepd and @oreillymedia** :
 - **Frequency of Tweets** : @dalepd tweets less often than @oreillymedia.
 - **Normalization** : When calculating the normalized score (retweets divided by total tweets), @dalepd ranks just below @oreillymedia.
 - **Implication** : Tim retweets @dalepd's content more frequently relative to the number of tweets they

post, despite @oreillymedia having a higher raw retweet count.

2. Visualization :

- **Bubble Chart (Figure 5-2) :**
 - **Y-Axis** : Represents the raw number of retweets for each user.
 - **Bubble Size** : Indicates the normalized retweet score compared to the user's total tweets.
- This visual helps illustrate the relationship between raw retweets and tweet frequency.

3. Exploring Tim's Retweeters :

- **Question of Influence** : Who retweets Tim the most?
- **Challenges** : Analyzing Tim's retweeters is complex due to his large following (~1.5 million), but can be simplified by focusing on a smaller, targeted population.

4. Measuring Influence :

- **Definition** : The number of retweets a user receives is a measure of their influence on Twitter.
- **Influence Indicators** : High retweet counts relative to tweets suggest strong influence; low retweets indicate weak influence.
- The concept highlights the importance of engagement in evaluating social media effectiveness.

Conclusion

Understanding retweet dynamics and measuring influence are essential for analyzing social media interactions. The comparison of normalized scores reveals deeper insights into user engagement, while focusing on Tim's retweeters can provide a clearer picture of his influence.

Notes on Measuring Influence and Retweet Analysis

Overview : This section discusses the relationship between followers and retweets on Twitter, emphasizing the importance of the tweet-to-retweet ratio as a measure of influence.

Key Concepts

1. Follower vs. Retweet Paradox :

- It is possible to have many followers but few retweets.
- Typically, **followers** and **retweets** come from being interesting and influential.

2. Tweet-to-Retweet Ratio :

- A **ratio of 1** indicates strong influence, meaning every tweet is retweeted.
- Values closer to **0** suggest weaker influence.
- Achieving a perfect ratio is unlikely due to conversational dynamics (e.g., @replies).

3. Twitter API Limitations :

- The **statuses/retweets_of_me** resource provides insights into which tweets have been retweeted, but

access may be restricted.

- Alternative methods must be used for analysis.

4. Example Code: the `tweet__count_retweets_by_others` .PY :

- **Purpose** : Calculates how often tweets have been retweeted.
- **Key Components** :
 - **Imports** : Utilizes `couchdb` for database interaction and `prettytable` for output formatting.
 - **Database Connection** : Connects to a specified CouchDB database and handles errors.
- **Mapper Function** : `retweetCountMapper(doc)` :
 - Extracts the `retweet_count` and yields it for processing.
- **Reducer Function** : `summingReducer(keys, values, rereduce)` :
 - Sums the counts of retweets.

5. Output :

- The result will show the number of tweets and their respective retweet counts, formatted in a chart.

Conclusion

Understanding the dynamics between followers and retweets, along with calculating the tweet-to-retweet ratio, is essential for assessing influence on Twitter. The provided example code demonstrates how to effectively analyze retweet data using CouchDB.

Notes on Retweet Analysis Results

Overview : This section describes how to analyze and present retweet data using Python, focusing on the retweet count of a user's tweets.

Key Concepts

1. Data Synchronization :

- **View Sync** : The code syncs the defined view in the CouchDB database to ensure it reflects the latest data.

2. Table Setup :

- **Fields** : Defines the columns as 'Num Tweets' and 'Retweet Count' .
- **PrettyTable** : Utilizes this library for a formatted display of results.

3. Data Aggregation :

- Initializes counters for total retweets, number of tweets, and tweets with zero retweets.
- Iterates through the retweet data sorted by retweet count.

4. Data Processing :

- **Counts Updates** :
 - If the retweet count is "100+" , it adds a value of 100 times the count.

- If the count is **0** , it increments the zero retweets counter.
- Otherwise, it adds the actual retweet count.
- **Total Tweets** : Keeps track of the total number of tweets processed.

5. Output Display :

- Prints the number of tweets that were retweeted at least once, the tweet-to-retweet ratio, and total retweets generated.
- Uses a formatted table to present retweet counts.

6. Results Overview (Figure 5-3) :

- Displays a compact chart with a logarithmic scale for better visualization.
- **Key Metrics** :
 - Out of over **3,000 tweets** , **2,536** were retweeted at least once (approximately a **0.80 ratio**).
 - Generated over **50,000 retweets** total, indicating a factor of about **16** .

7. Distribution Insights :

- The results follow a **power law** distribution, showing that a small number of tweets achieved high retweet counts.
- Notably, **533 tweets** received no retweets, while others received significant engagement.

Conclusion

The analysis highlights Tim's substantial influence on Twitter, confirming his status as a key information source with a high level of retweet engagement. The metrics gathered provide valuable insights into user interaction and content virality.

Notes on Hashtags and Folksonomy

Overview : This section explores the significance of hashtags in tweets and introduces the concept of folksonomy in the context of social media.

Key Concepts

1. Value of Hashtags in Tweets :

- Tweets containing **hashtags** are considered more valuable because they incorporate aggregatable information.
- The presence of hashtags indicates a user's intent to connect knowledge and understand the power of information.
- **Usage Analysis** :
 - Users averaging **2+ hashtags per tweet** are likely more engaged and informed.
 - Conversely, users with an average of **0.1 hashtags per tweet** may show less interest in leveraging information effectively.

2. What is a Folksonomy? :

- A **folksonomy** is a system for collaboratively tagging and classifying content on the web.
- It combines the concepts of "folk" (people) and "taxonomy" (classification).
- **Taxonomy vs. Ontology** : While taxonomy refers to hierarchical classification, ontology deals with the relationships between concepts.
- **Decentralized Classification** : A folksonomy allows users to assign tags to content, creating a collective intelligence mechanism for organizing information.

Conclusion

Understanding the role of hashtags enhances the perception of tweet value, while the concept of folksonomy highlights how collaborative tagging contributes to information organization on the web. Both concepts underscore the importance of user engagement and the collective effort in classifying digital content.

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Notes on Computing Average Hashtags per Tweet

Overview : This section describes how to calculate the average number of hashtags in tweets using a map/reduce approach.

Key Concepts

1. Objective :

- Calculate the **average number of hashtags** per tweet by counting total hashtags and total tweets separately, then dividing the two.

2. Code Structure :

- The code is written in Python and uses **CouchDB** to handle tweet data.

3. Database Connection :

- Connects to a specified CouchDB database and handles errors if the database is not found.

4. Mapper Function : `entityCountMapper(doc)` :

- Checks if the tweet document has an **entities** field.
- If not, it imports the **twitter_text** library to extract entities from the tweet text.
- **Entity Extraction** :
 - **User Mentions** : Extracts mentioned user screen names and stores them in `entities['user mentions']` .
 - **Hashtags** : Extracts hashtags and reformats the field names to match the production Twitter API, storing them in `entities['hashtags']` .
 - **URLs** : Extracts URLs and adds them to `entities['urls']` .

5. Output :

- The total number of hashtags and tweets will be calculated through two separate map/reduce phases, enabling the final computation of the average hashtags per tweet.

Conclusion

This method efficiently computes the average number of hashtags per tweet by leveraging entity extraction and the map/reduce framework. It highlights the importance of properly structuring data for analysis in social media research.

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Notes on Counting Hashtags and Tweets

Overview : This section explains how to compute the average number of hashtags per tweet using a map/reduce methodology, focusing on non-reply tweets.

Key Concepts

1. Mapper Function for Hashtags :

- `entityCountMapper(doc)` :
 - Checks if the tweet document contains an **entities** field.
 - Uses the **getEntities** function to extract user mentions, hashtags, and URLs from the tweet text.
 - If hashtags exist, it yields the count of hashtags.

2. Reducer Function :

- `summingReducer(keys, values, rereduce)` :
 - Sums the values (number of hashtags) provided by the mapper.

3. View Definition :

- Creates a view named `count_hashtags` for counting hashtags and syncs it with the database.

4. Counting Non-Reply Tweets :

- A new **mapper function** checks if a tweet is a direct reply (starts with '@').
 - If it is a reply, it yields 0; otherwise, it yields 1.
- This counts the total number of tweets that are not replies.

5. Average Calculation :

- The total number of hashtags and the total number of non-reply tweets are fetched from the database.
- The average number of hashtags per tweet is calculated as:
$$\text{Average} = \frac{\text{Total Hashtags}}{\text{Total Tweets}}$$

$$\text{Average} = \frac{\text{Total Tweets}}{\text{Total Hashtags}}$$

6. Results :

- For the recent data analyzed, it shows that Tim averages about **0.5 hashtags per tweet** that is not a direct reply, indicating he includes hashtags in about half of his tweets.

Conclusion

Including hashtags regularly enhances the visibility of tweets in Twitter's search index and contributes to the evolving folksonomy . Future analyses could explore hyperlink entities to further understand user interests, laying the groundwork for text mining techniques discussed in later chapters.

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Juxtaposing Latent Social Networks: #JustinBieber vs. #TeaParty

Overview : This section explores the discovery of new insights from Twitter data by analyzing the latent social networks surrounding two distinct hashtags: #JustinBieber and #TeaParty .

Key Concepts

1. Data Mining and Knowledge Discovery :

- Data mining allows for the extraction of valuable insights from large datasets.
- The phrase "**knowledge is power**" highlights the importance of understanding information in today's data-rich environment.

2. Objective :

- The goal is to investigate the connections and similarities between the **#TeaParty** and **#JustinBieber** hashtags.
- By asking the question, "What do #TeaParty and #JustinBieber have in common?" we can uncover latent social networks.

3. Data Collection Method :

- Use Twitter's search API to gather a focused dataset of tweets related to the chosen hashtags.
- **Example 5-14** shows how to collect approximately **1,500 tweets** (the maximum from the search API) and store them in **CouchDB** .
- The script can be modified to run over time for larger datasets, or the **streaming API** can be considered for continuous data collection.

4. Example Code :

- The provided code snippet in **Example 5-14** outlines the process for harvesting tweets:
 - **SEARCH TERM** : The hashtag being searched.
 - **MAX PAGES** : Limits the number of pages to retrieve (15 in this case).
 - **KW** : Contains parameters for the search, including the count of tweets returned per request.

Conclusion

This exercise not only reveals the social dynamics surrounding different topics but also emphasizes the potential for analysis within vast Twitter datasets. By applying similar metrics to these networks, we can gain deeper insights into the behavior and connections of Twitter users across diverse interests.

Collecting Tweets for Hashtags: #JustinBieber and #TeaParty

Overview : This section describes how to collect and analyze tweets related to specific hashtags, using CouchDB to store the data for later analysis.

Key Steps in the Process

1. Setup for Data Collection :

- Define the search term using `SEARCH TERM` .
- Connect to the CouchDB server running on `localhost:5984` .
- Create a database named based on the search term (e.g., `search-teaparty`), handling duplicates if the database already exists.

2. Twitter API Interaction :

- Use the Twitter API to fetch tweets, specifically from the **search domain** .
- Loop through up to **15 pages** of results, updating the CouchDB with each batch of tweets retrieved.
- Print the number of tweets fetched to keep track of progress.

3. Escaping Special Characters :

- When running queries in a terminal, certain characters like the hashtag (`#`) may need to be escaped (e.g., `\#TeaParty`) to ensure correct interpretation by the shell.

Analyzing Co-occurring Entities

1. Entity Analysis :

- To understand the characteristics of the crowds associated with each hashtag, analyze the entities (like user mentions, hashtags, etc.) that appear in the aggregated tweets.
- This analysis provides insights into the topics and discussions prevalent in each group.

2. CouchDB Usage :

- After collecting data for both hashtags, you should have two separate CouchDB databases: `search-justinbieber` and `search-teaparty` .
- Utilize these databases to perform further analysis, such as comparing the frequency of entities that co-occur in tweets for both topics.

3. Frequency Analysis :

- Generate tables (e.g., Tables 5-3 and 5-4) that display entities appearing more than **20 times** for each hashtag.
- Use visualizations (e.g., Figure 5-4) to illustrate the distribution of entity frequencies, aiding in the comparison of the two crowds.

Conclusion

This approach not only allows for effective data collection from Twitter but also sets the stage for deeper analysis of social interactions and interests linked to specific topics. By examining the entities present in tweets, you can gain valuable insights into the conversations surrounding different hashtags.

Analyzing Tweet Entities for #TeaParty

Overview : The analysis focuses on the most frequent entities (hashtags) found in tweets related to #TeaParty , using a logarithmic scale for better readability of frequency values.

Most Frequent Entities

1. Key Findings :
- The table below lists the hashtags associated with the #TeaParty movement, showing how often each hashtag appears in relevant tweets.

Table 5-3: Most Frequent Entities in #TeaParty Tweets

Entity	Frequency
#teaparty	2834
#tcot	2426
#p2	911
#tlot	781
#gop	739
#ocra	649
#sgp	567
#twisters	269
#dnc	175
#tpp	170
#GOP	150
#iamthemob	123
#ucot	120
#libertarian	112
#obama	112
#vote2010	109
#TeaParty	106
#hhrs	104

Entity	Frequency
#politics	100
#immigration	97
#cspj	96
#acon	91
#dems	82
#palin	79
#topprog	78
#Obama	74
#tweetcongress	72
#jcot	71
#Teaparty	62
#rs	60
#oilspill	59
#news	58

Conclusion

- The table illustrates a **variety of hashtags** associated with the **#TeaParty** , indicating the broad range of discussions and topics within this movement.
- The **logarithmic scale** helps make frequency differences clearer, especially given the extremes in the data. This analysis provides a valuable understanding of the social dynamics and interests among the participants in the **#TeaParty** conversation.

Analyzing Tweet Entities for #TeaParty

Overview : This section continues the analysis of entities associated with the #TeaParty movement, detailing additional hashtags and mentions found in tweets.

Additional Frequent Entities

1. **Key Findings :**
- Below is a list of additional hashtags and user mentions related to the **#TeaParty** discussion, along with their frequencies.

Table: Additional Frequent Entities in #TeaParty Tweets

Entity	Frequency
#glennbeck	54
#FF	47
#liberty	47
@welshman007	45
#spwbt	44
#TCOT	43
http://tinyurl.com/24h36zq	43
#rnc	42
#military	40
#palin12	40
@Drudge Report	39
@ALIPAC	35
#majority	35
#NoAmnesty	35
#patriottweets	35
@ResistTyranny	34
#tsot	34
http://tinyurl.com/386k5hh	31
#conservative	30
#AZ	29
#TopProg	29
@JIDF	28
@STOPOBAMA2012	28
@TheFlaCracker	28
#palin2012	28
@thenewdeal	27
#AFIRE	27
#Dems	27
#asamom	26
#GOPDeficit	25
#wethepeople	25
@andilinks	24
@RonPaulNews	24
#ampats	24
#cnn	24

Conclusion

- The table highlights a **diverse array of hashtags** and **user mentions** tied to the **#TeaParty** , reflecting the movement's various topics and key figures.
- Analyzing these entities provides insights into the broader conversations happening within the **#TeaParty** community, revealing connections and shared interests among participants.

Analyzing Tweet Entities for #JustinBieber

Overview : This section focuses on the entities associated with tweets containing the #JustinBieber hashtag, highlighting popular topics and mentions.

Frequent Entities in #JustinBieber Tweets

1. **Key Findings :**
- The following table lists the most common hashtags and user mentions found in tweets related to **#JustinBieber** , along with their frequencies.

Table: Frequent Entities in #JustinBieber Tweets

Entity	Frequency
#justinbieber	1613
#JustinBieber	1379
@lojadoaltivo	354
@ProSieben	258
#JUSTINBIEBER	191
#Proform	191
http://migre.me/TJwj	191
#Justinbieber	107
#nowplaying	104
@justinbieber	99
#music	88
#tickets	80
@ Yassi	78
#musicmonday	78
#video	78
#Dschungel	74

Conclusion

- The table highlights a **variety of hashtags** and **user mentions** associated with **#JustinBieber** , showcasing the topics that engage his audience.
- The frequency of entities reflects the **popularity of music** and events related to Bieber, indicating a vibrant conversation around his brand and content.

Analysis of Hashtags in Tweets for #JustinBieber

Overview : This section examines the entities associated with tweets containing the #JustinBieber hashtag, highlighting their frequencies and providing insights into the nature of the conversations around the topic.

Frequent Entities in #JustinBieber Tweets

1. Key Findings :
- The following table lists the most common hashtags and user mentions in tweets related to **#JustinBieber** , along with their frequencies.

Table: Frequent Entities in #JustinBieber Tweets

Entity	Frequency
#Celebrity	42
#beliebers	38
#BieberFact	38
@JustBieberFact	32
@TinselTownDirt	32
@rheinzeitung	28
#WTF	28
http ://tinyurl .com /343kax4	28
#Telezwerg	26
#Escutando	22
#justinBieber	22
#Restart	22
#TT	22
http ://bit .ly /aARD4t	21
http ://bit .ly /b2Kc1L	21
#bieberblast	20
#Eclipse	20
#somebodytolove	20

Observations

- **Entity Distribution** : The **#TeaParty** tweets show a significantly broader distribution in terms of the number of unique entities and hashtags, suggesting a more diverse conversation compared to the more focused nature of **#JustinBieber** tweets.
- **Content Richness** : The entities related to **#TeaParty** reflect a range of political topics, such as **#oilspill** , **#Obama** , and **#palin** , indicating a richer context. In contrast, **#JustinBieber** entities largely consist of variations of the hashtag itself and are less focused.
- **Cultural Context** : This difference in content is expected, as **#TeaParty** deals with political issues, while **#JustinBieber** is more centered on pop culture and entertainment.
- **User Mentions** : Notably, some user entities like **@lojadoaltivo** and **@ProSieben** rank higher than the official

@justinbieber account, suggesting that other accounts play a significant role in discussions around Bieber.

Conclusion

- The analysis highlights distinct characteristics between the two hashtags, with **#TeaParty** showcasing a complex and politically charged conversation, while **#JustinBieber** reflects a more simplified and entertainment-focused dialogue. This difference is essential for understanding the dynamics of social networks on Twitter.

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Comparing Hashtags in Tweets for #JustinBieber and #TeaParty

Overview : This section explores the average number of hashtags present in tweets related to #JustinBieber and #TeaParty , providing insights into the differences in how these two topics are discussed on Twitter.

Key Points

1. Co-occurring Entities :

- Many entities associated with **#JustinBieber** tweets are often non-English words or user mentions related to the **entertainment industry** . This reflects a cultural context focused on pop culture.

2. Average Hashtags per Tweet :

- To analyze the average number of hashtags per tweet for both topics, Example 5-13 demonstrates how to calculate this from the **search-justinbieber** and **search-teaparty** databases.
- The results show that:
 - **#JustinBieber** tweets average about **1.95 hashtags per tweet** .
 - **#TeaParty** tweets average around **5.15 hashtags per tweet** .
- This means that **#TeaParty** tweets contain approximately **2.5 times more hashtags** than **#JustinBieber** tweets.

3. Significance of Findings :

- While the difference is notable, it's important to recognize that this data comes from the most recent ~3,000 tweets provided by Twitter for each hashtag.
- Having these **quantifiable results** allows for further exploration and reassessment over time, as they provide a solid foundation for analyzing trends in social media conversations.

Conclusion

- The analysis indicates that tweets about **#TeaParty** are more hashtag-rich compared to those about **#JustinBieber** , reflecting the different nature of discussions surrounding political topics versus entertainment. This information is valuable for understanding engagement patterns in social media.

Analyzing Retweets for #JustinBieber and #TeaParty

Overview : This section examines the frequency of retweets for tweets related to #JustinBieber and #TeaParty . Retweets can indicate the influence and informational value of tweets.

Key Points

1. Folksonomies in #TeaParty :

- Twitter users discussing **#TeaParty** exhibit a strong belief in **folksonomies** —a system where content is organized and tagged for easy access.
- This community shows a vested interest in making their tweets easily searchable and referenced by data analysts.

2. Retweet Analysis :

- Retweets are often seen as a measure of a tweet's influence. Tweets that are **highly retweeted** tend to be more **informative** or **editorial** in nature.
- To analyze retweet behavior, a working set of search results was examined, focusing on users who frequently retweet content related to both hashtags.

3. Most Frequent Retweeters of #TeaParty :

- A selection of users who retweeted **#TeaParty** tweets at least **10 times** includes:
 - **@teapartyleader** : 10 retweets
 - **@dhrxsol1234** : 11 retweets
 - **@HCReminder** : 11 retweets
 - **@ObamaBallBuster** : 11 retweets
 - **@spitfiremurphy** : 11 retweets
 - **@GregWHoward** : 12 retweets
 - **@BrnEyeSuss** : 13 retweets
 - **@Calroofer** : 13 retweets
 - **@grammy620** : 13 retweets
 - **@Herfarm** : 14 retweets
 - **@andilinks** : 16 retweets
 - **@c4Liberty** : 16 retweets
 - **@FloridaPundit** : 16 retweets
 - **@tlw3** : 16 retweets
 - **@Kriskxx** : 18 retweets
 - **@crispix49** : 19 retweets
 - **@JIDF** : 19 retweets
 - **@libertyideals** : 19 retweets

Conclusion

- The analysis of retweets provides insight into which topics resonate more with users and indicates the level of

Retweet Analysis of #TeaParty vs. #JustinBieber

Overview : This section compares the frequency of retweets for tweets associated with #TeaParty and #JustinBieber , revealing differences in engagement within these communities.

Key Points

1. Most Frequent Retweeters for #TeaParty :

- Several users consistently retweeted **#TeaParty** content, with frequencies including:
 - **@blogging_tories** : 20 retweets
 - **@Liliaep** : 21 retweets
 - **@STOPOBAMA2012** : 22 retweets
 - **@First_Patriots** : 23 retweets
 - **@RonPaulNews** : 23 retweets
 - **@TheFlaCracker** : 24 retweets
 - **@thenewdeal** : 25 retweets
 - **@ResistTyranny** : 29 retweets
 - **@ALIPAC** : 32 retweets
 - **@Drudge_Report** : 38 retweets
 - **@welshman007** : 39 retweets

2. Most Frequent Retweeters for #JustinBieber :

- The most active retweeters for **#JustinBieber** include:
 - **@justinbieber** : 14 retweets
 - **@JesusBeebs** : 16 retweets
 - **@LeePhilipEvans** : 16 retweets
 - **@JustBieberFact** : 32 retweets
 - **@TinselTownDirt** : 32 retweets
 - **@ProSieben** : 122 retweets
 - **@lojadoaltivo** : 189 retweets

3. Retweet Statistics :

- An analysis of approximately **3,000 tweets** for each topic reveals:
 - **#TeaParty** : About **1,335** tweets are retweets.
 - **#JustinBieber** : About **763** tweets are retweets.
- This means **#TeaParty** has nearly **twice as many** retweets compared to **#JustinBieber** .
- Additionally, **#TeaParty** shows a longer tail with over **400 total retweets** , while **#JustinBieber** has **131 total retweets** .

4. Engagement Insights :

- The data suggests that **#TeaParty** users tend to retweet more consistently than those in the **#JustinBieber** community.
- However, among **#JustinBieber** users, there are notable outliers who retweet significantly more than their peers.

5. Visual Representation :

- Figure 5-5 provides a chart comparing retweet frequencies for both hashtags. The y-axis uses a **logarithmic scale** to enhance readability.

Conclusion

- The analysis indicates that the **#TeaParty** community is more engaged in retweeting than the **#JustinBieber** community, reflecting the differing interests and behaviors of each group on Twitter. This information is valuable for understanding how social media engagement varies across different topics.

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Overlap Between Entities in #TeaParty and #JustinBieber Tweets

Overview : This section examines the overlap of entities between tweets containing **#TeaParty** and **#JustinBieber** . Understanding this overlap can reveal insights into the intersection of these two distinct communities on Twitter.

Key Points

1. Defining Overlap :

- The goal is to identify the **logical intersection** of entities found in both **#TeaParty** and **#JustinBieber** tweets. This means determining which entities are common to both sets.

2. Methodology :

- Instead of adapting existing code, we can leverage previously written scripts to collect and analyze data efficiently.
- By using scripts to output the entity results into files, we create a manageable way to compute overlaps.

3. Script Setup :

- Assuming a **Unix-like shell** , a sample bash script can be used to capture and sort entities from both hashtags: **bash** Copy code

```
#!/bin/bash
mkdir -p out
for db in teaparty justinbieber; do
python the_tweet__count_entities_in_tweets .py search- $db 0 | \
tail +3 | awk '{print $2}' | sort > out/ $db .entities done
```
- This script creates a directory called **out** , processes the tweets from both hashtags, and saves sorted entities into files named **teaparty.entities** and **justinbieber.entities** .

4. Computing the Intersection :

- After capturing the entities, you can use a separate Python script to compute the intersection of the two entity files. This allows for a straightforward comparison of entities.

5. Benefits :

- This method not only accomplishes the analysis but also produces files that are easy to review and share, facilitating further exploration and collaboration.

Conclusion

- By analyzing the overlap of entities between **#TeaParty** and **#JustinBieber** , we can gain valuable insights into how these communities interact or share common themes, enriching our understanding of Twitter dynamics.

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Example 5-15: Computing the Intersection of Lines in Files

Purpose : This script helps identify common entities shared between two or more files by computing their logical intersection.

Key Components of the Script

1. File Reading :

- The script takes multiple file names as input arguments and reads their contents, storing each file's lines in a set for easy comparison.

2. Data Storage :

- A dictionary named `data` stores the sets of lines from each file, using the file names as keys.

3. Intersection Calculation :

- The script iterates through the sets and computes the intersection of the lines. This means it identifies lines that are present in both files.

4. Output :

- It constructs a message displaying the common items found across the specified files and prints each common line.

Script Example

python Copy code

```
# -*- coding: utf-8 -*- """ Read in 2 or more files and compute the logical intersection of the lines in them """ import sys
data = {} for i in range ( 1 , len (sys.argv)): data[sys.argv[i]] = set ( open (sys.argv[i]).readlines()) intersection = set ()
keys = data.keys() for k in range ( len (keys) - 1 ): intersection = data[keys[k]].intersection(data[keys[k + 1 ]]) msg =
'Common items shared amongst %s:' % ' , ' .join(keys).strip() print (msg) print ( '-' * len (msg)) for i in intersection: print
(i.strip())
```

Example 5-16: Sample Results from Intersection Computation

Common Entities Found : The entities shared between #JustinBieber and #TeaParty include:

- #lol
- #jesus
- #worldcup
- #teaparty
- #AZ
- #milk
- #ff
- #guns
- #WorldCup
- #bp
- #News
- #dancing
- #music
- #glennbeck
- <http://www.linkati.com/q/index>
- @addthis
- #nowplaying
- #news
- #WTF
- #fail
- #toomanypeople

Summary

This script efficiently identifies and lists common hashtags and entities shared between tweets about #TeaParty and #JustinBieber . The results, while somewhat predictable, provide insight into the intersection of these two distinct Twitter communities.

Shared Hashtags Between #TeaParty and #JustinBieber

Common Hashtags :

- #WorldCup
- #worldcup
- #oilspill
- #teaparty
- #glennbeck
- #jesus
- #catholic

Observations:

1. **Popularity** : It's expected to find popular topics like **#WorldCup** and **#oilspill** among shared hashtags.
2. **Surprising Entries** : The presence of hashtags like **#teaparty** , **#glennbeck** , **#jesus** , and **#catholic** might be unexpected for those unfamiliar with the **Tea Party** movement.
3. **Correlation Analysis** : Further analysis can explore how often these hashtags appear in each group's tweets, revealing stronger correlations between the two topics.
4. **Frequency Distribution** : Notably, none of the common entities appear in the top 20 frequent hashtags for **#JustinBieber** , indicating they are less common overall.

Humor in Commonality:

- The inclusion of hashtags like **#WTF** and **#fail** illustrates a universal experience of frustration, linking diverse groups through shared emotions.

Visualizing Twitter Data

Tag Clouds:

- **Tag Clouds** are an effective method for visualizing tweet entities, showcasing the frequency of hashtags.
- Various **tag cloud widgets** are available online, simplifying the visualization process.

Customizing Visualizations:

- Instead of a standard tag cloud, consider using a **Flash-based rotating tag cloud** , such as **WP-Cumulus** .
- **Input Format** : To use WP-Cumulus, generate a simple input format consisting of frequency distributions, formatted as a JSON structure.

Example Implementation:

The following example illustrates how to produce a JSON structure suitable for WP-Cumulus:

python Copy code

```
# Example 5-17: Generating JSON for WP-Cumulus # This adaptation feeds in a list of [term, URL, frequency] tuples for the tag cloud. # Note: URLs can be linked to a service that displays relevant tweets.
```

Summary:

The analysis of common hashtags between **#TeaParty** and **#JustinBieber** reveals unexpected connections and opportunities for deeper exploration. Visualizing these connections through tag clouds offers a compelling way to present the data, making it accessible and engaging.

Generating Interactive Tag Clouds with WP-Cumulus

Overview:

To create an interactive tag cloud that visualizes tweet entities, we can utilize WP-Cumulus . This involves extracting data from tweets stored in CouchDB and formatting it for the tag cloud display.

Key Components:

1. **CouchDB** : A NoSQL database where tweets are stored.
2. **Entity Extraction** : The process of identifying key components (like hashtags and user mentions) within tweets.

Code Example:

Here's a breakdown of how to generate data for the tag cloud:

Python Script (the `tweet__tweet_tagcloud_code .py`):

python Copy code

```
# -*- coding: utf-8 -*- import os import sys import json import couchdb from cgi import escape # Parameters DB = sys.argv[ 1 ] # Database name MIN_FREQUENCY = int( sys.argv[ 2 ] ) # Minimum frequency of entities to include HTML_TEMPLATE = '../web code /wp cumulus /tagcloud template .html' # Path to the HTML template # CouchDB server connection server = couchdb.Server( 'http://localhost:5984' ) db = server[DB] # Function to map entities to tweet documents def entityCountMapper ( doc ): if not doc.get( 'entities' ): import twitter_text # Library to extract entities def getEntities ( tweet ): extractor = twitter_text .Extractor(tweet[ 'text' ]) # Extract entities from tweet text entities = { 'user mentions ': extractor.extract mentioned_screen_names_with_indices (), 'hashtags': extractor.extract hashtags_with_indices (), } # Adjust field names to match Twitter API for ht in entities[ 'hashtags' ]: ht[ 'text' ] = ht[ 'hashtag' ]
```

Key Functions:

- **entityCountMapper (doc)** : Maps entities found in tweets to their corresponding documents. It checks if the tweet has entities and uses the **twitter_text** library to extract:
 - **User Mentions** : Identifies mentioned users.
 - **Hashtags** : Extracts hashtags and adjusts their field names to match the Twitter API format.

Visualization:

- The output can be used with the **WP-Cumulus** template to create a visually appealing tag cloud.
- This tag cloud can display the frequency of each entity, with size variations based on their occurrence.

Summary:

By extracting entities from tweets in CouchDB and utilizing a structured format, we can generate an interactive tag cloud with WP-Cumulus . This provides an engaging way to visualize Twitter data, making it easy to see which topics are trending based on frequency.

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Generating Hashtag and User Mention Counts from Tweets

Overview:

This section focuses on how to extract and count entities like hashtags and user mentions from tweets, allowing for their visualization in a tag cloud.

Key Functions and Code Breakdown:

1. Entity Extraction :

- The script extracts **user mentions** , **hashtags** , and **URLs** from each tweet.
- For each user mention and hashtag, it yields a tuple containing:
 - The entity (e.g., '@username' or '#hashtag').
 - A list of document IDs where the entity appears.

2. Mapping Function :

- `entityCountMapper(doc)` :
 - Checks if the tweet document has entities.
 - Extracts entities using the **twitter text** library.
 - Appends found entities to the tweet document.

3. Reducer Function :

- `summingReducer(keys, values, rereduce)` :
 - If reducing results, it sums up the values.
 - If re-reducing, it simply returns the sum of previously reduced values.

4. Creating a View Definition :

- A view is created using **ViewDefinition** , linking the mapper and reducer functions to allow for counting entities by document.

5. Extracting Frequencies :

- The script queries the database to get entity frequencies, grouping results for easier processing.

6. Formatting Output for Tag Cloud :

- The results are sorted and filtered based on a defined **minimum frequency** .
- Each term is escaped for HTML compatibility.

7. Weighting Terms for Display :

- A weighting function calculates the font size based on the frequency of each entity, ensuring more frequently mentioned entities appear larger.

8. Substituting Data into HTML Template :

- The generated data is inserted into the **WP-Cumulus** HTML template, preparing it for display.

Summary:

The process involves extracting and counting important entities from tweets, such as hashtags and user mentions , to visualize them in a tag cloud. This approach not only facilitates data analysis but also enhances user engagement by displaying relevant topics in a visually appealing format.

Creating and Visualizing a Tag Cloud from Tweet Data

Overview:

This section details the process of generating a tag cloud to visualize entities extracted from tweets, using Python and HTML.

Key Steps and Components:

1. Output Directory Setup :

- The script checks if the output directory '**out**' exists; if not, it creates one.

2. Writing the HTML File :

- The generated HTML content for the tag cloud is written to a file in the '**out**' directory.
- The filename is derived from the **HTML template** used.

3. Opening the Tag Cloud :

- The newly created tag cloud HTML file is automatically opened in the web browser for easy viewing.

4. Weighting Tag Frequencies :

- A formula is employed to adjust the size of tags in the cloud based on their frequency.
 - Tags are scaled between **MIN FONT_SIZE** and **MAX FONT_SIZE** .
 - This linear squashing takes into account the frequency of each tag and the overall range of frequencies.
- Variations of this formula may include logarithmic adjustments for better representation.

5. Tag Cloud Design Insights :

- Kevin Hoffman's paper, "**In Search of the Perfect Tag Cloud** ," is recommended for deeper insights into tag cloud design choices.

6. HTML Template :

- The **tagcloud template .html** file is a simple adaptation that utilizes string substitution to insert data.
- It contains script tags that manage the visual rendering of the tag cloud.

7. Visual Differences :

- Figures comparing tag clouds for **#JustinBieber** and **#TeaParty** illustrate the density of terms.
 - The **#TeaParty** tag cloud is noticeably more crowded, reflecting the diverse topics associated with it.
- Tag clouds visually summarize the information, making it easier to identify key themes.

8. Further Visualization Options :

- Users can create interactive visualizations using tools like **Google Chart Tools** for more dynamic presentations.

Summary:

This process outlines how to create a tag cloud from tweet data, focusing on visualizing entity frequencies and providing insights into the data's thematic structure. The approach emphasizes both practicality in generating the visualization and the aesthetic considerations in tag cloud design.

Visualizing Community Structures in Twitter Search Results

Overview : This section expands on previous comparisons of **#JustinBieber** and **#TeaParty** by visualizing the community structures of Twitter users associated with these hashtags.

Key Concepts:

- **Community Structures** : Analyzing how users and entities (like mentions and hashtags) connect within Twitter.
- **Friendship Computation** : Determining relationships among tweet authors and associated entities.

Steps to Visualize Connections:

1. **Collect Unique Users** : Identify unique tweet authors and user mentions from the **#TeaParty** and **#JustinBieber** datasets stored in CouchDB.
2. **Harvest Friend IDs** : Use Twitter's **/friends/ids** API to gather friend IDs for these screen names.

Applications:

- This visualization technique not only provides insights into **#JustinBieber** and **#TeaParty** but can also be adapted for other hashtag comparisons.

Note : The specific code for these processes is not provided but can be derived from earlier chapters.

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Visualizing Twitter Friendships and Connections

Process Overview : This section outlines the steps to analyze friendships among Twitter users using their friend IDs and visualize the resulting network.

Key Steps:

1. **Resolving Screen Names** :
 - Use Twitter's **/users/lookup** resource to convert friend IDs into screen names.
 - Note: There is no direct method for looking up screen names; friend IDs must first be collected.
2. **Constructing a Graph** :
 - Create a **networkx.Graph** by mapping friendships.
 - An **edge** is formed between two **nodes** (users) if there is a mutual friendship.
3. **Analyzing and Visualizing** :
 - Analyze the constructed graph and visualize the connections.

Results:

- The script produces a **pickled graph file** that can be accessed in the Python interpreter for further exploration.
- This analysis uses data from approximately **3,000 tweets** for both **#JustinBieber** and **#TeaParty** .
- Outputs include the **degree** of each node (number of connections), which is visualized as a column chart (see Figure 5-8).

Note : The script's details are not included in the text but are available online, utilizing logic from earlier examples.

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Ad-Hoc Graph Analysis Using Python

Overview : This example demonstrates how to perform ad-hoc analysis on Twitter friendship graphs using the `networkx` library.

Key Steps:

1. Importing NetworkX :

- Begin by importing the **networkx** library: python Copy code `import networkx as nx`

2. Loading Graph Data :

- Load the previously saved graph files for **#TeaParty** and **#JustinBieber** : python Copy code `teaparty = nx.read_gpickle ("out/search-teaparty.gpickle") justinbieber = nx.read_gpickle ("out/search-justinbieber.gpickle")`

3. Analyzing the Tea Party Graph :

- Retrieve the number of **nodes** and **edges** : python Copy code `teaparty.number_of_nodes () , teaparty.number_of_edges ()` # Output: (2262, 129812)
- Calculate the **density** of the graph (how interconnected it is): python Copy code `nx.density(teaparty)` # Output: 0.0508

4. Analyzing the Justin Bieber Graph :

- Retrieve the number of **nodes** and **edges** : python Copy code `justinbieber.number_of_nodes () , justinbieber.number_of_edges ()` # Output: (1130, 1911)
- Calculate the **density** : python Copy code `nx.density(justinbieber)` # Output: 0.0030

5. Degree of Nodes :

- The **degree** of a node indicates the total number of edges connected to it. This can be sorted for analysis: python Copy code `sorted (nx.degree(teaparty))` # Output omitted for brevity

Visualization:

- **Figure 5-8** shows a comparison of the **connectedness** of the two graphs by plotting the sorted degree of each node.

Note : The degree of a node in an undirected graph is simply the total number of edges linked to it.

Analyzing Graph Metrics Without Visualization

Overview : Understanding graph metrics is essential, especially when visual representations are not available. This analysis focuses on the #TeaParty and #JustinBieber graphs.

Key Findings:

1. Importance of Metrics :

- It's crucial to interpret numbers and relationships in graphs without relying on visual aids. Complex graphs often require significant time to visualize effectively.

2. Comparison of Graphs :

- The **density** and the **ratio of nodes to edges** (users to friendships) in the **#TeaParty** graph are significantly higher than in the **#JustinBieber** graph.
- The **high connectedness** of nodes in the **#TeaParty** graph is particularly noteworthy.

3. Contextual Differences :

- **#TeaParty** represents an intense political movement with a smaller, more concentrated audience.
- In contrast, **#JustinBieber** is a broad entertainment topic with international appeal.

4. Distribution Insights :

- The overall **distribution** and **shape of the curve** for the **#TeaParty** graph provide insights into the strong connections among its users.

Graph Representation:

- A simple 2D visual can help illustrate the connectedness of both hashtags, with each edge representing a friendship.

Graphviz Usage:

- For **nix users** , you can generate a Graphviz output with: bash Copy code `nx.drawing.write dot`
- **Windows users** may need to manually create the DOT output.

Sample Command for SFDP : To produce a layout for a dense graph, you can use the following command:

bash Copy code

```
$sfdp -Tpng -Oteaparty -Nfixedsize=true -Nlabel="" -Nstyle=filled -Nfillcolor=red -Nheight=0.1 -Nwidth=0.1 -
```

```
Nshape=circle -Gratio=fill -Goutputorder=edgesfirst -Gsize= '10!' -Goverlap=prism teaparty.dot
```

Note : Figure 5-9 shows a visual representation of the connectedness between the #JustinBieber (left) and #TeaParty (right) Twitter users.

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Closing Remarks on Tweet Data Analysis

Overview : The potential for analyzing tweet data is vast and creative exploration can reveal even more possibilities. This chapter offers just a glimpse into what can be done.

Key Ideas for Further Exploration:

1. Similarity Metrics :

- Develop a **similarity metric** to compare Twitter users or groups.
- Create user profiles and measure how well individual users fit these profiles.
- Example: Analyze the frequency of certain **hashtags** or **keywords** (like "LOL" or "OMG") in **#JustinBieber** tweets versus more intellectual hashtags in **#gov20** .

2. Celebrity Tweet Analysis :

- Identify celebrities with low tweet diversity but high tweet volume. Are they just ramblers?
- Contrast this with celebrities who use many **hashtags** . What comparisons can you draw between the two groups?

3. Personal Analysis :

- If you have a Twitter account, analyze your own tweet patterns.
- Compare your tweeting style to that of other users across different metrics.

4. Twitter Lists API :

- Investigate the **Twitter Lists API** to profile members of specific lists.
- Explore latent social networks, such as identifying political boundaries between followers of different lists (e.g., @timoreilly/healthcare vs. @timoreilly/gov20).

5. Temporal Tweet Analysis :

- Analyze tweet volume or content based on the **time of day** .
- Use tools like the **SIMILE Timeline** for visualization.

6. Real-Time Communication :

- Take advantage of Twitter's **streaming API** for near real-time data access.
- Explore **tweepy** as a user-friendly streaming client.

Conclusion : The opportunities in tweet analytics are vast, with potential for substantial insights and even business opportunities focused on answering ad-hoc queries.

Chapter 6: LinkedIn - Clustering Your Professional Network

Overview : This chapter focuses on techniques for analyzing data on LinkedIn, a leading social networking site for professionals. The insights gained can be applied beyond LinkedIn to other platforms with similar data export capabilities.

Key Points:

1. Building a Professional Network :

- It's recommended to develop a professional network on LinkedIn while exploring the techniques in this chapter.
- Even without a LinkedIn profile, many methods discussed can be useful for other platforms that allow data export, like address books.

2. Unique Nature of LinkedIn Data :

- LinkedIn data differs from typical social networks; users are generally more focused on **business opportunities** and maintaining professional appearances.
- Profiles typically include detailed information about **business relationships** , **job history** , and **educational backgrounds** .

3. Data Privacy Considerations :

- LinkedIn's API is designed with a focus on privacy, limiting access to sensitive information about connections.
- Unlike other platforms, you cannot check if two arbitrary users are connected, as this data is considered private and valuable.
- The management team believes that protecting professional networking data is crucial to preventing exploitation, as stated by D.J. Patil, LinkedIn's Chief Scientist.

4. Adapting to Data Limitations :

- Due to restrictions on access to connection data, the analysis requires a different approach.
- Users must focus on the data available for their direct connections, posing unique questions about this information.

Conclusion : The chapter encourages a thoughtful exploration of LinkedIn's professional data, highlighting the importance of privacy and the need for innovative questioning to extract valuable insights from the available information.

Clustering Techniques for LinkedIn Data

Overview : This section introduces fundamental clustering techniques to analyze LinkedIn data, allowing users to address specific queries related to their professional network.

Key Queries Addressed:

1. Similarity of Connections :

- Identify connections that are most similar based on criteria like **job title** .

2. Company Insights :

- Find connections who have worked at companies of interest to you.

3. Geographical Distribution :

- Analyze where your connections are located geographically.

Motivation for Clustering:

- The rich data available on LinkedIn provides significant opportunities for answering these queries effectively.

Common Themes in Clustering:

1. Measuring Similarity :

- Assessing similarity between values (e.g., job titles, company names) is often necessary.
- Additional approaches to measuring similarity are discussed in Chapter 7.

2. Complexity of Clustering :

- To cluster items using a similarity metric, each member must be compared to every other member.
- For **n** members, this requires approximately **n²** similarity computations, referred to as an **O(n²)** problem.
- O(n²) problems become impractical for large datasets, potentially requiring excessive time to compute.

Approximate Matching Problem:

- This discussion relates to the **approximate matching problem** , also known as fuzzy matching or deduplication, which is a well-studied but challenging issue across many industries.

Conclusion : Understanding these clustering techniques and the underlying complexities is essential for effectively leveraging LinkedIn data to enhance insights into your professional network.

Techniques for Approximate Matching in Data Mining

Overview : Approximate matching is crucial in data mining across various industries, as it addresses the challenges posed by semi-standardized relational data.

Importance of Approximate Matching:

- **Wide Applicability** : Relevant in sectors like **defense intelligence** , **fraud detection** , and **local businesses** .
- Companies often collect data without predefined values for every field, leading to **semi-standardized data** or "dirty records."

Causes of Dirty Records:

- **Improper Database Design** : User interfaces may not restrict input, allowing varied data entry.
- **Data Entry Variations** : Common issues include:
 - **Misspellings**
 - **Abbreviations** (e.g., "Google" vs. "Google, Inc.")
 - **Case Differences**

Challenges with LinkedIn Data:

- LinkedIn users enter professional information as free text, resulting in variations that complicate data analysis.
- To analyze connections (e.g., where they work), it's essential to standardize company names by addressing common variations and suffixes (e.g., ", Inc.", ", LLC").

Data Access Methods:

1. **Exporting Address Book Data** :
 - Basic information like **name** , **job title** , **company** , and **contact information** can be exported.
2. **Using the LinkedIn API** :
 - Provides comprehensive access to all details visible to authenticated users on LinkedIn.

Data Preparation:

- For initial exercises, using exported address book data (in **CSV** format) is sufficient.
- It's recommended to use the **"Outlook CSV"** format for compatibility with Python's **csv module** for parsing data.

Conclusion : Understanding and implementing approximate matching techniques is essential for effectively analyzing LinkedIn data, addressing the challenges of dirty records and data variations.

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Example 6-1: Normalization of Company Suffixes

Overview : This example demonstrates how to normalize company names by stripping common suffixes from an address book data file, ensuring cleaner data for analysis.

Code Breakdown:

1. Imports :

◦ Libraries :

- `sys` : To handle command-line arguments.
- `nltk` : For natural language processing.
- `csv` : To read CSV files.
- `prettytable` : For displaying results in a table format.

2. Setup :

- The script expects a CSV file as input from the command line: `CSV FILE = sys.argv[1]` .

3. Transformations :

- A list of known **abbreviations and suffixes** to remove:

- `' , Inc. '`
- `' , Inc '`
- `' , LLC '`
- `' , LLP '`

4. Reading CSV Data :

- Opens the CSV file and reads its contents into a list of dictionaries (`contacts`).
- Extracts and cleans the company names, ignoring any empty entries.

5. Normalization Process :

- For each company name, applies the transformations to remove specified suffixes.
- Uses a nested loop to replace each suffix in the company names.

6. Frequency Distribution :

- Creates a frequency distribution of the cleaned company names using `nltk.FreqDist` .
- Constructs a table to display companies that occur more than once, showing their frequency.

7. Output :

- The results are printed in a nicely formatted table using `PrettyTable` .

Additional Complexity:

- While the script handles basic suffix removal, more complex company names (e.g., **O'Reilly Media**) can have multiple representations:
 - O'Reilly & Associates
 - O'Reilly Media
 - O'Reilly, Inc.
 - O'Reilly
- Job titles also present similar challenges due to their variability. An example table lists distinct job titles in the technology industry, highlighting the need to standardize and normalize job titles as well.

Conclusion:

Normalizing company names and job titles is crucial for accurate analysis, especially when dealing with varied representations of the same entity. More sophisticated methods may be required to handle complex variations effectively.

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Job Titles in the Technology Industry

Common Job Titles :

1. **CEO** (Chief Executive Officer)
2. **Developer**
3. **Software Developer**
4. **Software Engineer**
5. **CTO** (Chief Technical Officer)
6. **President**
7. **Senior Software Engineer**

These titles demonstrate the variety of roles within a technology organization, each with potential variations that need normalization for analysis.

Exporting LinkedIn Connections

Steps to Export Connections :

1. Click on **Contacts** in your LinkedIn profile.
2. Select **My Connections** from the pop-up menu.

3. Click on the **"Export connections"** link on the next screen.

This process allows you to download your connections' information, facilitating data analysis and clustering efforts.

Conclusion

Understanding job titles and properly exporting LinkedIn connections are essential for effectively analyzing professional networks and exploring clustering opportunities.

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Normalizing Job Titles

Challenges in Job Title Normalization :

- Creating a list of **aliases** for job titles (e.g., **CEO** vs. **Chief Executive Officer**) is manageable but impractical for more varied titles like **Software Engineer** and **Developer** .
- A better approach is to allow **human oversight** in the data cleaning process, where experts review and refine data before automated processing. This ensures higher quality control.

Clustering Contacts by Job Title

Reasons to Analyze LinkedIn Data :

- To assess if your networking efforts are connecting you with the **right people** .
- To target contacts likely to fit a specific **socioeconomic profile** for business inquiries.

Standardizing and Counting Job Titles

Initial Steps :

- Begin by counting job titles to understand their distribution.
- Normalize common job titles to reduce variability in data.

Frequency Analysis :

- Analyze the frequency of job titles and individual **tokens** within those titles. This can reveal nuances in how titles are used.

Example Code: Standardizing Job Titles

python Copy code

```
# -*- coding: utf-8 -*- import sys import nltk import csv from prettytable import PrettyTable CSV_FILE = sys.argv[ 1 ]
```

- Use the `prettytable` library for formatted output of the job title frequencies.

Conclusion

Standardizing job titles and counting their occurrences are essential steps in effectively clustering your LinkedIn contacts, enabling better networking and business strategies.

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Code for Normalizing Job Titles

Transformations for Standardization :

- A list of common **abbreviations** is created to standardize job titles:
 - **Sr.** and **Sr** → **Senior**
 - **Jr.** and **Jr** → **Junior**
 - **CEO** → **Chief Executive Officer**
 - **COO** → **Chief Operating Officer**
 - **CTO** → **Chief Technology Officer**
 - **CFO** → **Chief Finance Officer**
 - **VP** → **Vice President**

Reading and Processing CSV Data

- **CSV Reader** : The code uses `csv.DictReader` to read the CSV file containing contact information, separating values by commas.
- **Contact List** : It creates a list called `contacts` containing all the rows from the CSV file.

Handling Job Titles

- **Title Extraction** : The code processes job titles, splitting any combined titles (e.g., "President/CEO") into separate entries.
- **Abbreviation Replacement** : Each title is normalized using the `transforms` list to ensure consistency.

Frequency Analysis

1. Title Frequency :

- A frequency distribution of job titles is created using `nltk.FreqDist`.
- Titles that appear more than once are added to a **PrettyTable** for easy visualization.

2. Token Frequency :

- The code also splits titles into individual **tokens** (words) to analyze word frequency.
- Tokens are counted and those with a frequency greater than one and a length greater than two are displayed in another **PrettyTable**.

Summary

- The code effectively reads job title data from a CSV, normalizes it by handling combined titles and standardizing common abbreviations, and displays frequency counts for both titles and tokens, providing insights into the structure of job titles within a professional network.

Frequency Distribution of Job Titles and Tokens

Overview : The analysis provides a frequency distribution for both complete job titles and the individual words (tokens) within those titles. This helps to understand how job titles are structured and their commonalities.

Sample Results (Example 6-3):

- **Job Titles** :
 - **Chief Executive Officer** : 16 occurrences
 - **Senior Software Engineer** : 12 occurrences
 - **Owner** : 9 occurrences

- **Software Engineer** : 9 occurrences

- **Tokens :**

- **Engineer** : 44 occurrences
- **Software** : 31 occurrences
- **Senior** : 27 occurrences
- **Manager** : 26 occurrences
- **Chief** : 24 occurrences
- **Officer** : 12 occurrences
- **Director** : 11 occurrences

Insights :

- The most common **exact job title** is "**Chief Executive Officer.**"
- The most frequent **token** is "**Engineer,**" which appears in multiple titles (e.g., "Senior Software Engineer" and "Software Engineer"). This indicates that while specific titles may differ, the term "Engineer" is prevalent across various roles.

Motivation for Approximate Matching

This frequency analysis underscores the necessity for approximate matching or clustering algorithms . Such tools help in grouping similar job titles, providing clearer insights into the data structure.

Common Similarity Metrics for Clustering

The choice of an appropriate similarity metric is crucial for clustering job titles effectively. Various string similarity metrics exist, and the selection should align with the specific objectives of the analysis.

Key Considerations :

- The nature of the **data** and the **objective** of the clustering will determine the most suitable similarity metric to use.

This groundwork prepares for exploring different metrics that can be applied to job title clustering.

Key Similarity Metrics for Clustering Job Titles

1. Edit Distance (Levenshtein Distance)

- **Definition** : Edit distance measures the minimum number of operations (insertions, deletions, substitutions) required to transform one string into another.
 - **Example** : To change "dad" to "bad," it takes one substitution (replace 'd' with 'b'), giving an edit distance of **1** .
- **Implementation** : NLTK provides this functionality via `nltk.metrics.distance.edit_distance` .
- **Computation Complexity** : The actual calculation can be computationally expensive, typically requiring around **M*N** operations for strings of lengths **M** and **N** .

2. n-gram Similarity

- **Definition** : An **n-gram** is a sequence of **n** consecutive tokens from a text, forming a structure for analyzing text patterns.
- **Bigrams** : A specific case where **n = 2** , and you compute pairs of adjacent tokens.
 - **Example** : For the title "Chief Executive Officer," the bigrams are:
 - `(None, 'Chief'), ('Chief', 'Executive'), ('Executive', 'Officer'), ('Officer', None)` .
- **Common Bigrams** : Similarity between two strings can be assessed by counting shared bigrams.
 - **Example** : For "Chief Executive Officer" and "Chief Technology Officer," they share **2 bigrams** .
- **Padding** : Using `pad_right = True` and `pad_left = True` helps include leading and trailing tokens in comparisons.

3. Jaccard Distance

- **Definition** : This metric quantifies the similarity between two sets by comparing their intersections and unions.
 - **Formula** : Jaccard similarity = $\frac{|Set1 \cap Set2|}{|Set1 \cup Set2|}$.
- **Interpretation** : It indicates the proportion of shared items relative to the total distinct items across both sets.

Summary

These metrics— edit distance , n-gram similarity , and Jaccard distance —are essential tools for clustering job titles and analyzing textual data. Each provides a different approach to measuring similarity and understanding relationships within the data.

Key Distance Metrics for String Similarity

1. Jaccard Similarity

- **Definition** : Jaccard similarity measures how similar two sets are by comparing their intersections and unions.
- **Formula** : Jaccard Distance = $\frac{|X \cup Y| - |X \cap Y|}{|X \cup Y|}$ $\text{Jaccard Distance} = \frac{|\text{X} \cup \text{Y}| - |\text{X} \cap \text{Y}|}{|\text{X} \cup \text{Y}|}$ Jaccard Distance = $\frac{|X \cup Y| - |X \cap Y|}{|X \cup Y|}$
 - Where **X** and **Y** are sets of items (e.g., unigrams, bigrams).
- **Implementation** : Available in NLTK as `nltk.metrics.distance.jaccard_distance` .

2. MASI Distance

- **Definition** : The MASI distance is a modified version of Jaccard similarity that gives a smaller distance score when there is partial overlap between sets.
- **Formula** : MASI Distance = $1 - \frac{|X \cap Y|}{\max(|X|, |Y|)}$ $\text{MASI Distance} = 1 - \frac{|\text{X} \cap \text{Y}|}{\max(|\text{X}|, |\text{Y}|)}$ MASI Distance = $1 - \frac{|X \cap Y|}{\max(|X|, |Y|)}$
- **Implementation** : Available in NLTK as `nltk.metrics.distance.masi_distance` .

Example Usage

- A code snippet compares various sets of items to compute both Jaccard and MASI distances: python Copy code

```
from nltk.metrics.distance import jaccard_distance , masi_distance
from prettytable import PrettyTable
fields = [ 'X' , 'Y' , 'Jaccard(X,Y)' , 'MASI(X,Y)' ]
pt = PrettyTable(fields=fields)
for z in range ( 4 ):
    X = set ()
    for x in range (z, 4 ):
        Y = set ()
        for y in range ( 1 , 3 ):
            X.add(x)
            Y.add(y)
            pt.add_row ([ list (X), list (Y), round (jaccard_distance (X, Y), 2 ), round (masi_distance (X, Y), 2 )])
pt.printt()
```

Key Observations

- When sets are completely **disjoint** or **equal** , the **MASI distance** equals the **Jaccard distance** .
- With **partial overlap** , the **MASI distance** is generally higher than the **Jaccard distance** .
- Consider which metric— **MASI** or **Jaccard** —is more suitable for your specific task of clustering job titles.

Conclusion

Both Jaccard similarity and MASI distance are valuable for assessing the similarity of strings, particularly in contexts like job title clustering. Choosing the right metric depends on the nature of the data and the specific requirements of your analysis.

Comparing Jaccard and MASI Distances

Overview

- **Jaccard Distance** and **MASI Distance** are metrics used to assess the similarity between sets.
- The **distance** is crucial for determining how similar two items (like job titles) are, especially in clustering contexts.

Sample Results

- **Table 6-2** provides comparisons between Jaccard and MASI distances for small sets, illustrating how the two metrics differ based on their calculations.

X	Y	Jaccard (X,Y)	MASI (X,Y)
[0]	[1]	1.0	1.0
[0]	[1, 2]	1.0	1.0
[0, 1]	[1]	0.5	0.5
[0, 1]	[1, 2]	0.67	0.5
[0, 1, 2]	[1]	0.67	0.67
[0, 1, 2]	[1, 2]	0.33	0.33
[0, 1, 2, 3]	[1]	0.75	0.75
[0, 1, 2, 3]	[1, 2]	0.5	0.5
[1]	[1]	0.0	0.0
[2]	[1]	1.0	1.0
[3]	[1]	1.0	1.0

Key Observations

- **Equal and Disjoint Sets** : When sets are either identical or completely disjoint, both distances yield the same value.
- **Partial Overlap** : When sets partially overlap, the **MASI distance** is often higher than the **Jaccard distance** , indicating different sensitivities to partial matches.

Next Steps

- The next section will focus on using the **MASI similarity metric** to cluster job titles, leveraging its strengths in handling partially overlapping terms.

Conclusion

Understanding how Jaccard and MASI distances compare helps in selecting the right metric for clustering tasks. As data exploration continues, experimenting with various similarity metrics will further refine insights into the data being

analyzed.

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Clustering Job Titles Using a Greedy Heuristic

Overview

The purpose of this code is to cluster job titles by analyzing their similarities using a greedy heuristic based on MASI distance . This approach normalizes titles and groups similar ones together for easier analysis.

Key Components of the Code

- **Imports :**
 - Libraries such as `sys` , `csv` , and `nltk.metrics.distance` for necessary functionalities.
- **Constants :**
 - **CSV FILE** : Input file for contact data.
 - **DISTANCE THRESHOLD** : Set at **0.34** , it determines when two job titles are considered similar enough to be clustered.
 - **DISTANCE** : Defined as `masi distance` , which is the metric used for measuring similarity.

Main Function: `cluster_contacts_by_title`

1. Transformations :

- A list called **transforms** is created to standardize common abbreviations for job titles (e.g., "Sr." becomes "Senior").

2. Separators :

- **separators** : Defined as `['/', 'and', '&']` , these are used to split combined job titles (like "President/CEO").

3. Reading CSV :

- The contacts are read from the specified CSV file into a list called **contacts** .

4. Normalizing Titles :

- For each contact:
 - If the **Job Title** is empty, it assigns an empty list to **Job Titles** .
 - If not empty, it:
 - Initializes a list called **titles** with the **Job Title** .
 - Splits the titles using defined separators.
 - Normalizes each title by applying transformations from the **transforms** list.
 - Finally, assigns the processed titles back to the contact's **Job Titles** .

Summary

This code systematically processes job titles by standardizing them and creating a list of normalized titles for each contact. The use of MASI distance as a clustering metric allows for effective grouping of similar job titles, which facilitates better analysis of professional connections. The greedy approach ensures that decisions about clustering are made based on the defined threshold, helping to create meaningful categories from potentially diverse job titles.

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Clustering Job Titles: Detailed Process

Key Steps in the Code

1. Collecting Unique Titles :

- All normalized titles are combined into the list **all titles** .
- This list is converted to a **set** to remove duplicates, ensuring each title is unique.

2. Creating Clusters :

- An empty dictionary **clusters** is initialized to hold clustered titles.
- For each **title1** in **all titles** :
 - An empty list is created for **title1** in **clusters** .
 - A nested loop iterates through **all titles** to compare **title2** with **title1** .
 - If **title2** is already clustered with **title1** or vice versa, it is skipped.
 - The **MA SI distance** between the two titles is calculated using the defined **DISTANCE** function.
 - If the distance is less than the **DISTANCE THRESHOLD** , **title2** is added to the list for **title1** in **clusters** .

3. Flattening Clusters :

- Clusters are filtered to include only those with more than one title, creating a simplified list.

4. Grouping Contacts by Cluster :

- A new dictionary **clustered contacts** is initialized to store contacts associated with each cluster.
- For each cluster:
 - A unique key is created from the tuple of titles.
 - Each contact is checked against the titles in the cluster.
 - If a contact's job title matches any title in the cluster, the contact's name is added to that cluster in **clustered contacts** .

5. Displaying Results :

- The main block of code executes the clustering function and prints out the results.
- For each group of clustered titles:
 - The common titles are displayed.
 - **Descriptive terms** (words that are common across the titles) are calculated and printed.
 - The contacts in each cluster are listed below their corresponding titles.

Summary

This code efficiently clusters job titles based on MASI distance to highlight similarities. By first normalizing the job titles and then comparing them within a nested loop, it identifies clusters of related titles. The output provides a clear view of which contacts share similar roles, along with key descriptive terms that characterize the clusters. This process helps in understanding networking patterns and enhancing professional connections.

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Clustering Job Titles: Greedy Approach Explained

Overview of the Greedy Clustering Method

1. Greedy Grouping :

- The term "**greedy**" refers to the approach of assigning items to clusters as soon as a match is found, without considering whether a better fit may exist later.
- This method prioritizes efficiency and pragmatism, producing reasonable results quickly.

2. Importance of Similarity Heuristic :

- The choice of an effective **similarity heuristic** is crucial for accurate clustering.
- Fewer calls to the scoring function (which measures similarity) improve performance, as this reduces unnecessary calculations.

3. Labeling Clusters :

- Each cluster is assigned a meaningful label based on the **setwise intersection** of terms in the job titles within that cluster.
- This approach highlights common responsibilities among grouped individuals, making it easier to understand their roles.

Practical Applications of Clustering

- Clustering job titles helps identify individuals with similar job responsibilities, which can be beneficial for various scenarios, such as:
 - Organizing a **CEO Panel** for events.
 - Understanding professional connections to facilitate career moves.
 - Assessing whether you are well-connected within your field.

Sample Output

The expected results from this clustering method display grouped titles and key descriptive terms, illustrating how individuals share job functions. For example:

- **Common Titles** : Chief Executive Officer, Chief Finance Officer, Chief Technology Officer, Chief Operations Officer
- **Descriptive Terms** : Chief, Officer

This output provides a clear overview of the clustered titles and the individuals associated with them, enabling better networking and collaboration opportunities.

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Challenges of Scalable Clustering

Overview of the Current Clustering Method

- The current clustering approach involves a **nested loop** that compares job titles using a **DISTANCE** calculation.
- This method has a time complexity of $O(n^2)$, meaning the number of operations grows exponentially with the number of titles:
 - For 100 job titles, about **10,000** operations are needed.
 - For 10,000 job titles, the operations increase to **100,000,000**.

Scalability Issues

- **Nested Loops** : Comparing each title to every other title becomes impractical for large datasets, making the current method not scalable.
- As the number of titles (n) increases, the number of required comparisons grows rapidly, which can overwhelm system resources.

Seeking Efficient Algorithms

- To manage large datasets effectively, aim for an algorithm with a complexity of $O(k*n)$, where k is significantly smaller than n . This allows for a more manageable overhead.
- Many businesses use proprietary methods to achieve scalable record-matching, providing them with a competitive edge.

Alternative Approaches

- If an $O(n^2)$ algorithm is inadequate, consider variations like:
 - **Random Sampling** : Modify the nested loop to randomly select pairs for comparison, potentially reducing

the total number of operations.

Conclusion

Finding the right balance between performance and quality is challenging in data clustering. As datasets grow, innovative and scalable solutions become crucial to maintain efficiency without sacrificing accuracy.

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Improving Clustering Performance with Sampling

Overview of Sampling Techniques

- **Sampling** can significantly improve performance by reducing the number of comparisons needed in clustering algorithms.
- When using a sample size **k**, the runtime complexity can be reduced to $O(k \cdot n)$. However, if **k** approaches **n**, performance may revert to $O(n^2)$.

Example of Random Sampling

- Example 6-8 demonstrates how to implement a random sampling technique in the clustering code:
 - Instead of comparing every title, the inner loop runs a fixed number of times based on the sample size, reducing overall computation.

Binning Strategy

- Another effective approach is to **bin** the data:
 - Divide the dataset into **n bins** (typically less than or equal to the square root of the total number of items).
 - Perform clustering within each bin and then merge results.
 - For instance, clustering 1 million items into 1,000 bins of 1,000 items each reduces the operations from a trillion ($O(n^2)$) to a billion (1,000 comparisons per bin).

Alternatives to Reduce Dimensionality

- There are various methods beyond sampling and binning to handle high dimensionality and reduce computational burden:

- Techniques from **machine learning** often use **probabilistic models** and advanced sampling to tackle scaling issues.

Introduction to k-Means Clustering

- The next section will introduce **k-means** , a well-known clustering algorithm suitable for organizing data in multidimensional spaces.
- This method will be applied to cluster contacts based on **geographic location** later in the discussion.

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Intelligent Clustering and User Experience

Importance of Clustering

- **Intelligent clustering** focuses on enhancing user experiences through effective data organization, rather than just data-mining techniques.
- **Simple clustering** methods, like those based on job titles, can significantly improve user interaction by presenting data in a meaningful way.

Benefits of Clustering

- By using **meaningful similarity metrics** , clustering can yield intuitive data groups.
- A **hierarchical display** can help users quickly locate information, reducing the need for extensive searching.

Visualization with Tree Widgets

- Clustering results can be represented visually using tools like **tree widgets** , which provide a clear navigation structure.
- This approach allows for **faceted displays** , helping users filter search results easily.

Code Example for Navigation Display

- Creating a navigational display is simplified by modern **Ajax toolkits** and UI libraries.
- Example 6-9 illustrates how a basic **Dojo tree widget** can be set up with minimal code, enabling effective data presentation.

Summary

- The application of intelligent clustering techniques not only organizes data but also fosters a more compelling and efficient user experience, making it easier for users to engage with the information presented.

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Creating a Dojo Tree Widget for Clustering

HTML Structure

- The HTML template includes links to **Dojo CSS** for styling and the Dojo JavaScript library for functionality.
- The script imports necessary Dojo modules:
 - **ItemFileReadStore** for data storage.
 - **Tree** for creating the tree widget.
 - **parser** for parsing the HTML.

Data Integration

- The `data` variable will hold a **JSON structure** substituted by Python code, which provides the content for the tree widget.

Body Content

- The body includes two main components:
 - A **data store** (`jobsStore`) linked to the JSON data.
 - A **tree widget** (`mytree`) that displays the clustered contacts and opens nodes on click.

JSON Data Preparation

- Example 6-10 outlines how to transform the clustered contacts data into a JSON format suitable for Dojo.

JSON Structure

- The base structure contains:
 - A **label** for identification.
 - **temp items** to temporarily hold grouped items.
 - An **items** list to store the final output.

Data Processing

- For each set of titles in `clustered_contacts` :
 - Descriptive terms are extracted and updated.
 - Contacts are grouped by their descriptive terms.
- Each unique descriptive term creates a JSON entry, which includes:
 - The term and its count.
 - A list of corresponding contacts as **children** .

Summary

- This setup allows for a dynamic tree widget that visualizes clustered job titles effectively, enhancing user interaction with the displayed data.

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Creating and Displaying JSON Data

Finalizing the JSON Structure

- The line `data['temp_items'][descriptive_terms]}` finalizes the JSON structure for each descriptive term.
- The `temp_items` key is deleted to clean up the data before output.

Outputting HTML

- The code checks if an **output directory** called `out` exists; if not, it creates one.
- The **template path** (`TEMPLATE`) is defined, pointing to the HTML file structure.
- The **output path** (`OUT`) is set for the generated HTML file.

- The template is read into a variable, and the JSON data is inserted into the HTML using string formatting.

Opening the Result

- The resulting HTML file is opened in a web browser, displaying the tree structure.

Importance of User Experience

- Creating intuitive data displays enhances user engagement, encouraging users to explore more information and derive greater value from services offered.

Clustering Techniques Overview

Introduction to Clustering Methods

- Besides the **greedy clustering** approach introduced earlier, two other important techniques are:
 - **Hierarchical Clustering**
 - **k-Means Clustering**

Hierarchical Clustering

- **Definition** : A deterministic method that calculates the distance matrix between all items and groups them based on a minimum distance threshold.
- **Structure** : The clustering process results in a tree (dendrogram) that visually represents the relationships between items.
- **Agglomerative Nature** : This method is often referred to as **agglomerative** clustering because it merges individual items (leaves) into clusters (nodes) progressively.

Summary

- Understanding these clustering techniques is vital, as they are widely used in data analysis and can be implemented using available libraries. The chapter will focus more on **k-means clustering** but also acknowledges the significance of hierarchical clustering in practical applications.

Hierarchical Clustering vs. Greedy Clustering

Overview of Techniques

- **Hierarchical Clustering** differs from the **greedy heuristic** used in Example 6-6. Instead of grouping items based on immediate similarity, it builds a **hierarchical structure**.
- This approach may require **more wall clock time**, meaning it could take longer to run due to its comprehensive nature.

Time Complexity and Efficiency

- Both methods have a time complexity of $O(n^2)$, but hierarchical clustering only processes **half** of the distance matrix because the distance between two items (like job titles) is typically **symmetric**. This reduces the workload to $0.5 \cdot n^2$, which is more efficient.

Example Code for Hierarchical Clustering

- To implement hierarchical clustering, you would modify Example 6-6 as shown in Example 6-11:

python Copy code

```
# Import the HierarchicalClustering class from cluster import HierarchicalClustering # Define a scoring function def
score ( title1, title2 ): return DISTANCE( set (title1.split()), set (title2.split())) # Create an instance of
HierarchicalClustering with your data and scoring function hc = HierarchicalClustering(all_titles , score) # Cluster the
data based on a distance threshold clusters = hc.getlevel(DISTANCE_THRESHOLD ) # Filter out singleton clusters
(clusters with only one item) clusters = [c for c in clusters if len (c) > 1 ]
```

Linkage Methods in Hierarchical Clustering

- The **setLinkageMethod** function allows you to choose how distances between clusters are calculated:
 - **Shortest distance** (single linkage)
 - **Longest distance** (complete linkage)
 - **Average distance** (average linkage)

Visualization Options

- Different linkage methods can produce varied results depending on data distribution.
- **Figure 6-3** shows a visual representation of a professional network using:
 - A **radial tree layout** for space efficiency.
 - A **dendrogram** for hierarchical relationships.
- Choosing the right visualization depends on the data and intended insights.

Summary

- **Hierarchical Clustering** provides a structured approach to grouping data, which can be computationally intensive but offers nuanced results. By utilizing advanced techniques like symmetry in distance calculations and customizable linkage methods, you can effectively analyze and visualize complex datasets.

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Visualizing Hierarchical Clustering

- **Hierarchical Clustering** allows for understanding relationships between data at various levels of a tree structure, corresponding to each level of **agglomeration**.
- Visualizations, such as those shown in **Figure 6-3**, highlight this data effectively:
 - A **radial tree layout** on the left displays contacts clustered by job title.
 - A **dendrogram** on the right illustrates the same data, revealing intricate relationships.
- These visual tools help users uncover significant insights about their professional network.

K-Means Clustering Overview

- In contrast to **hierarchical clustering**, which is deterministic and has a time complexity of $O(n^2)$, **k-means clustering** operates with a more efficient time complexity of $O(k*n)$.
- This performance improvement means that while k-means may provide **approximate** results, they are often still effective for practical use.

Steps of K-Means Clustering

1. **Initialization** : Randomly select **k points** in the data space as initial cluster centroids (K_1, K_2, \dots, K_k).
2. **Assignment** : Assign each of the **n data points** to the nearest centroid (K_n), effectively forming **k clusters**. This requires **k*n comparisons**.

Summary

- **Hierarchical clustering** provides a detailed view of data relationships through visualizations, while **k-means clustering** offers a more scalable, albeit approximate, method for grouping data. Understanding these techniques is essential for effective data analysis and visualization.

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K-Means Clustering Steps

1. **Calculate Centroid** : For each of the **k clusters** , compute the **centroid** (mean) and update the cluster's centroid value (K_i) to this new value. This is where the term "**k-means**" comes from.
 2. **Reassignment** : Reassign each data point to the nearest centroid based on distance.
 3. **Iteration** : Repeat steps 1 and 2 until the clusters stabilize (i.e., members do not change). Typically, k-means converges in a few iterations.
- **Visualization** : **Figure 6-4** illustrates each step of this process, using a Java applet with 100 data points and k set to 3, showing how clusters form over nine steps.

Dimensionality and Effectiveness

- K-means can handle data in various dimensions, from **2D to 2000D** , but is most effective in **2D or 3D** scenarios.
- It is a **fast and efficient** clustering method for lower dimensions, producing reliable results.
- Choosing the correct value for **k** (number of clusters) is crucial, but it can be challenging to determine.

Fetching Extended Profile Information

- To enhance the earlier exercises, you'll want to utilize **LinkedIn APIs** to access more detailed data.
- The process involves:
 - **Registering** for authorization credentials on the LinkedIn developer site.
 - Following the **OAuth** authentication process to obtain an access token.
- Most of the detailed work will be simplified using the **linkedin Python module** , which you can install with **easy install python-linkedin** .

Summary

- K-means clustering is an effective method for grouping data points into clusters based on distance, with a clear iterative process. To fully leverage your professional network's data, you'll use LinkedIn APIs to gather richer profile information.

K-Means Clustering Overview

- **Figure 6-4** : This figure demonstrates the **progression of the k-means clustering algorithm** using **k=3** with a set of **100 data points** .

Key Points of K-Means Clustering

1. **Initialization** : The algorithm starts by randomly selecting **k initial centroids** .
2. **Cluster Assignment** : Each data point is assigned to the nearest centroid, creating **k clusters** .
3. **Centroid Calculation** : After assignment, the centroid of each cluster is recalculated as the mean of all points within that cluster.
4. **Iteration** : Steps 2 and 3 are repeated until the cluster assignments no longer change, indicating convergence.

Importance of the Visualization

- The visual representation in **Figure 6-4** illustrates how the clusters evolve over time and how data points shift between clusters during the algorithm's iterations.
- This helps users understand how k-means effectively groups similar data points together.

Summary

K-means is a powerful clustering technique that groups data points based on distance, and the visualization shows the algorithm's iterative process and final clustering results.

Steps to Get LinkedIn API Credentials

1. **Visit Developer Site** : Go to [LinkedIn Developer](#) .
2. **Access API Keys** : Click on "Your Stuff" and then select "API Keys" from the top menu.
3. **Create a New App** : Follow the prompts to create a new application.

4. **Set Up App Parameters** : Fill in the necessary parameters for your app.
5. **Note Credentials** : After setup, make sure to **record your API Key and Secret** for future use.

Using the LinkedIn API

- Once you have the **linkedin package** installed, you can use a provided script (Example 6-12) to log in and access your professional network through the API.

Note on OAuth Implementation

- As of **October 2010** , LinkedIn is transitioning to **OAuth 2** . The **linkedin module** (version 1.6) currently supports **OAuth 1.0a** as outlined in their documentation.

Summary

These steps guide you through obtaining API credentials from LinkedIn, enabling you to interact with their professional network programmatically. Make sure to stay updated on any changes to the API or authentication methods.

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Harvesting Extended Profile Information from LinkedIn

Example 6-12: Code Overview for LinkedIn Connections

This script allows you to access extended profile information of your LinkedIn contacts using the LinkedIn API.

Key Components

1. **Imports** :
 - Imports necessary libraries such as `os` , `sys` , `webbrowser` , and `cPickle` .
 - Imports the `linkedin` module for API interaction.
2. **API Key and Secret** :
 - Takes the **API Key** and **API Secret** as command-line arguments.
3. **Return URL** :

- Sets a **RETURN URL** for handling OAuth responses: `python Copy code RETURN_URL = 'http://miningthesocialweb.appspot.com/static/linkedin_oauth_helper.html'`

OAuth Dance Function

- **Function** : `oauthDance(key, secret, return_url)`
 - **Purpose** : Handles the OAuth authentication process.
- **Steps** :
 1. **Request Token** : Calls `api.requestToken()` to initiate the process.
 - If it fails, it prints the error message.
 2. **Authorization URL** : Gets the authorization URL via `api.getAuthorizeURL()` and opens it in a web browser.
 3. **User Input** : Prompts the user to enter the **PIN number** for verification.
 4. **Access Token** : Calls `api.accessToken(verifier=oauth_verifier)` to get the access token.
 - If this fails, it prints an error message.

Main Script Execution

1. **Authenticate** : Calls `oauthDance` to authenticate the user.
2. **Fetch Connections** :
 - If authentication is successful, it retrieves the user's connections with `api.GetConnections()`.
 - If authentication fails, it outputs an error message and exits the script.

Summary

This script demonstrates how to authenticate with LinkedIn's API and fetch extended profile information for your connections. Properly handling OAuth is crucial for secure access to user data. Make sure to replace the placeholder URLs and ensure your API credentials are valid before running the script.

Fetching Extended Profile Information from LinkedIn

Important Note : Using the LinkedIn API for fetching extended connections is considered "expensive." For more details, refer to the LinkedIn API documentation at [LinkedIn Docs](#).

Key Steps in the Code

1. Output Status :

- The code begins by printing a message indicating that extended connections are being fetched: python Copy code `print >> sys.stderr, 'Fetching extended connections...'`

2. Fetch Extended Connections :

- It retrieves detailed profiles for each connection using the `GetProfile` method: python Copy code `extended_connections = [api.GetProfile(member_id=c.id, url=None, fields=[...]) for c in connections]`
- **Fields Requested :**
 - first-name
 - last-name
 - current-status
 - educations
 - specialties
 - interests
 - honors
 - positions
 - industry
 - summary
 - location

3. Store Data :

- The code checks if an output directory exists, creating one if it doesn't: python Copy code `if not os.path.isdir('out'): os.mkdir('out')`
- It saves the fetched data into a file using `cPickle` : python Copy code `f = open('out/linkedin_connections.pickle', 'wb') cPickle.dump(extended_connections, f) f.close()`
- A message confirms that the data has been saved: python Copy code `print >> sys.stderr, 'Data pickled to out/linkedin_connections.pickle'`

OAuth Verification

- Unlike Twitter, LinkedIn requires a specified URL for capturing the OAuth verifier needed to authorize the client.
- A sample HTML template for extracting the OAuth verifier is provided in Example 6-13. This template demonstrates how to display the verifier for user convenience.

Summary

This segment of code outlines how to fetch extended profile information for LinkedIn connections, emphasizing the resource-intensive nature of this API usage. The fetched data is then stored efficiently using `pickle`. Understanding the OAuth process is crucial for successful API interaction, with a sample template available for reference.

1. OAuth Verifier Prompt :

- After setting up your OAuth process, you'll need to enter the following identifier in your terminal: `html Copy code < strong > < span id = "oauth_verifier " >`

2. Rate Limits :

- **Complex Rate-Throttling** : LinkedIn's rate limits are more intricate than those of other APIs:
 - **Total Daily Limit** : Each application has a maximum number of requests it can make per day.
 - **User-Specific Limits** : Individual users also face limits based on their usage.
 - **Developer Limits** : Developers may have additional constraints on their request volume.
 - **API-Specific Limits** : Different APIs have varying rate limits, especially between accessing personal data versus data from other users' networks.
- **Reset Timing** : If you exceed these limits, you must wait until midnight Pacific Standard Time (PST) for the limits to reset.

3. Fetching Profile Information :

- Example 6-12 shows how to retrieve "mini-profiles" of users using the `GetConnections` method and how to get full public profiles with `GetProfile` .
- Due to rate limits, avoid lengthy data collection processes, as it may take considerable time to gather data.

Geographically Clustering Your Network

1. Accessing Extended Profile Information :

- Now that you can fetch extended profile data from LinkedIn, you can apply clustering algorithms to analyze this data.

2. Visualization Techniques :

- **K-means Clustering** : This technique will be used to cluster your professional contacts visually on Google Earth.
- **Dorling Cartogram** : An alternative visualization method that resembles a bubble chart. It shows how many contacts live in each state without explicitly using a clustering algorithm. However, it still provides a geographic representation of your network.

3. Mapping with Google Earth :

- Visualizing your LinkedIn contacts on a map (or globe) can reveal how your connections are distributed geographically.
- You can analyze clusters based on:
 - Your contacts.
 - Distinct employers of your contacts.
 - Metro areas where your contacts reside.
- Each approach can yield valuable insights for different analytical purposes.

Summary

Understanding LinkedIn's rate limits is crucial for effective API usage, as they affect data retrieval capabilities. Once you've mastered profile fetching, you can utilize clustering algorithms to analyze and visualize your professional network, enhancing your understanding of connections across geographic locations.

Using the LinkedIn API for Geocoding Contacts

1. Fetching Location Information :

- The LinkedIn API allows you to obtain geographic information about your contacts, such as their metropolitan areas (e.g., "Greater Nashville Area"). This data can be processed (munged) to convert locations into geographic coordinates suitable for plotting in tools like Google Earth.

2. Steps to Get Started :

- **Parse Geographic Locations** : Extract the geographic location from each contact's public profile. Example 6-12 demonstrates how to fetch this information.
- **Geocode Locations** : Convert the parsed locations into coordinates using the `geopy` library. You may need to install it via `easy_install geopy`. Depending on your geocoder (like Google or Yahoo!), you might need to obtain an API key from the service provider.
- **Cluster Coordinates** : Use the `KMeansClustering` class from the `cluster` module to compute clusters based on the geocoded coordinates.
- **Create KML for Visualization** : Generate KML (Keyhole Markup Language) files that can be imported into Google Earth or other visualization tools.

3. Further Customization :

- After completing the initial setup as shown in Example 6-14, there are many possibilities for further analysis and visualization. The `linkedin_kml_utility` mentioned is a simple helper that facilitates the creation of KML files through XML manipulation. More details can be found on GitHub.
- For an alternative to Google Earth, you can use Google Maps by providing a URL pointing to your KML file, allowing for easy access to your visualized data.

Example Code Snippet (linkedin_geocode .py)

- The following elements are included in the example code:
 - Import necessary libraries: `os`, `sys`, `cPickle`, `HTTPError`, `geopy`, and `KMeansClustering`.
 - Utilize a helper function (`createKML`) to build the KML structure.
 - Define the number of clusters `K` and the geocoding API key from command-line arguments.

This streamlined process enables you to visualize your LinkedIn contacts geographically, enhancing your understanding of your professional network's distribution.

Geocoding LinkedIn Connections

1. Loading Data :

- The script begins by loading the saved connections data, which includes extended profile information. This data is obtained using the command-line argument `CONNECTIONS DATA`.

2. Setting Up Geocoding :

2. Setting up Geocoding :

- The output file for KML (Keyhole Markup Language) is specified as `clusters.kmeans.kml` .
- The `Yahoo` geocoder is initialized using an API key (`GEOCODING_API_KEY`).

3. Transforming Location Data :

- Some locations may need basic transformations for successful geocoding. Examples include:
 - Removing "Greater " and " Area".
 - Modifying "San Francisco Bay" to "San Francisco".
- Additional custom transformations may be necessary based on the dataset.

4. Counting Location Frequencies :

- A dictionary (`coords_freqs`) is created to tally the frequency of each location.
- For each location, if it's already in the dictionary, its count is incremented. If not, it proceeds to transform the location and perform geocoding.

5. Geocoding Process :

- The script tries to geocode each transformed location, using a loop to handle potential errors from the geocoding service (like HTTP errors).
- It attempts to geocode up to three times if errors are encountered, exiting if it fails after multiple attempts.
- For each successful geocode, the coordinates and frequency of that location are stored in the `coords_freqs` dictionary.

6. Optional Segmentation :

- The script suggests that you might want to segment locations by continent or country to avoid averaging coordinates from locations like oceans, ensuring more meaningful clustering results.

This process enables efficient geocoding of LinkedIn connections' locations, facilitating the analysis of geographic distribution in subsequent clustering tasks.

K-Means Clustering for LinkedIn Contacts

1. Preparing Data for K-Means :

- The **k-means algorithm** requires distinct points for each contact. To facilitate this, an **expanded list** of coordinates is created.
- For each location in `coords_freqs` , the latitude and longitude are paired with their frequency, resulting in repeated entries for each coordinate based on how many contacts share that location.

2. Constructing KML Items :

- **KML Items** are generated to represent these coordinates visually. Each item includes:
 - **Label** : The name of the location.
 - **Coordinates** : Formatted as `longitude,latitude` for compatibility with Google Earth.
- Additionally, each item can include the names of contacts associated with that location, formatted to show the first name and initial of the last name.

3. Clustering with KMeans :

- The **KMeansClustering** class is utilized to perform clustering on the expanded coordinates.
- The centroids (the central points of each cluster) are calculated using the `getclusters` method, which groups the contacts based on their locations.

4. Creating KML Output :

- Centroids are added to the KML items list, labeled as 'CENTROID' with their coordinates.
- A KML file is generated using the `createKML` function.
- The output directory is created if it doesn't exist, and the KML data is saved to a file named `clusters.kmeans.kml`.

5. Data Processing Notes :

- The location data from LinkedIn profiles, such as "Greater Nashville Area," often requires **munging** (data cleaning and transformation) to extract accurate city names. The approach may need adjustments based on specific data characteristics to ensure accuracy.
- Much of the code focuses on **data processing** leading to the visualization stage, with the key clustering logic residing in the KMeans class.

This process effectively organizes and visualizes LinkedIn connections based on geographical locations, enabling insightful analysis of the professional network's distribution.

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Visualizing and Analyzing Your Professional Network

1. Overview of Clustering :

- **Clustering contacts by location** allows you to easily identify where your professional connections live or work. This visual representation helps in understanding the geographical distribution of your network.

2. Centroid Calculation :

- The **centroids** of clusters represent the central points of the grouped contacts. This can be particularly useful for:
 - **Planning regional workshops or conferences** by determining optimal meeting locations based on where most contacts are located.
 - **Consulting purposes**, helping to identify convenient places to stay during travel.

3. Broader Applications :

- Geographic clustering can be applied to various scenarios, including:
 - **Mapping professionals** by job roles or socioeconomic status, allowing for targeted outreach or networking.
 - **Supply chain management**, where understanding the location of suppliers and customers is critical.
 - Solving **Travelling Salesman problems**, optimizing routes based on geographical data.

4. Considerations for Clustering :

- Clusters can span **countries or continents**, making it essential to consider international locations when planning meetings or events.
- Visualizations not only enhance understanding of your network but also facilitate strategic decision-making based on location data.

By leveraging geographic clustering and centroid analysis, you can gain valuable insights into your professional network and explore various practical applications.

Mapping Your Professional Network with Dorling Cartograms

1. Introduction to Dorling Cartograms :

- A **Dorling Cartogram** is a type of visualization that uses circles to represent geographic areas, placed where those areas are located on a map.
- **Circle properties** such as **circumference** and **color** encode information, allowing for intuitive data interpretation.

2. Advantages of Dorling Cartograms :

- They provide a **geographically clustered bubble chart** that helps users visualize data without distorting geographic boundaries.
- The uniform shape (circle) and the intuitive use of **area and color** make it easier to understand the underlying data.

3. Other Visualization Options :

- Protovis, the HTML5 visualization toolkit, also offers various other geographic visualizations, including:
 - **Heatmaps** : Visual representations showing the density of data points.
 - **Symbol maps** : Maps that use symbols to represent data values.
 - **Choropleth maps** : Maps where areas are shaded in proportion to the value of a variable.

4. Creating a Dorling Cartogram :

- After geocoding your LinkedIn contacts, a minor adjustment to your script can produce a Dorling Cartogram visualization.
- Example code is available on GitHub, which can be enhanced with features like **event handlers** to display connection information when a user clicks on a state.

5. Closing Remarks :

- This chapter explored key **clustering techniques** and their applications to your LinkedIn network.
- While foundational, many additional analyses can be performed with your LinkedIn data. Consider exploring correlations between job locations and educational backgrounds or analyzing relocation trends.
- Remember, there are many other tools available in your toolkit beyond just geographic data and clustering.

By leveraging Dorling Cartograms and other visualization techniques, you can gain deeper insights into your professional network, making data analysis both informative and engaging.

Exploring Geo Data with Geodict

1. Geodict Framework :

- **Geodict** is an emerging open framework designed for working with geographic data. It offers various tools and functionalities for data analysis and visualization.

2. Dorling Cartogram Visualization :

- **Figure 6-7** illustrates a **Dorling Cartogram** , which represents the number of colleagues in each state using circles.
- The **size of each circle** corresponds to the number of colleagues residing in that state.
- **Color coding** can enhance this visualization by representing additional variables, such as:
 - **Unemployment rates** in each state.
 - **Job turnover rates** based on your colleagues' extended profile information.

3. Benefits of Visualization :

- Using tools like Dorling Cartograms can help convey complex data intuitively, making it easier to identify trends and insights within your professional network.

In summary, exploring geo data through frameworks like Geodict and visualizations such as Dorling Cartograms can provide valuable insights into professional networks, enhancing data analysis and decision-making.

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Chapter 7: Google Buzz - TF-IDF, Cosine Similarity, and Collocations

1. Introduction to Text Mining :

- This chapter marks the **transition into text mining** , focusing on analyzing **textual information** in documents.
- Earlier chapters concentrated on **structured or semi-structured data** (like microformats and hashtags).
- Key concepts introduced include **Information Retrieval (IR)** fundamentals: **TF-IDF** , **cosine similarity** , and **collocation detection** .

2. Data Source - Google Buzz :

- **Google Buzz** is the primary data source due to its **social nature** , ease of data harvesting, and relevance to the social web.
- Towards the chapter's end, there will be an exploration of **Gmail data** .

3. Future Topics :

- Upcoming chapters will cover **blog data mining** and various text analytics techniques, including:
 - **Entity extraction** .
 - **Automatic generation of abstracts** .

4. Order of Topics :

- The sequence (Buzz before blogs) is chosen to create a cohesive narrative, showcasing Buzz as a hybrid between Twitter and blogs.

5. Use of Existing Tools :

- The chapter aims to utilize existing analysis tools rather than create them from scratch.
- It will include "deep dives" into foundational topics essential for understanding text mining.
- The **Natural Language Toolkit (NLTK)** will provide many necessary tools and APIs for text mining.

Key Concepts:

- **Text Mining** : Analyzing unstructured data to extract useful information.
- **TF-IDF** : A statistical measure used to evaluate the importance of a word in a document relative to a collection of documents.
- **Cosine Similarity** : A metric used to measure how similar two text documents are, based on the angle between their vector representations.
- **Collocation Detection** : Identifying words that frequently occur together to reveal relationships in text.

This chapter sets the stage for understanding and applying text mining techniques in various contexts, emphasizing practical applications and existing technologies.

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Overview of Text Analytics and NLTK

1. Text Analytics Complexity :

- Text analytics is a **diverse and complex field** , but mastering key fundamentals can yield significant results with minimal effort.
- This chapter focuses on those **fundamental concepts** essential for text mining.

2. Natural Language Toolkit (NLTK) :

- A comprehensive introduction to NLTK is not included, but further resources are available:
 - **Natural Language Processing with Python: Analyzing Text with the Natural Language Toolkit** (O'Reilly).
 - Available online and in print at O'Reilly .

Google Buzz as a Data Source

1. Google Buzz Overview :

- Google Buzz combines features of both **Twitter and blogs** .
- Users with a **Gmail account** also have access to Buzz, making it accessible to a wide audience.
- Buzz posts can be as lengthy as blog entries but maintain a more **informal tone** similar to tweets.

2. Functionality :

- Buzz allows users to quickly share ideas with minimal formatting.
- Users can customize their Buzz settings to integrate Twitter activity into their Buzz feeds.

3. API and Data Mining :

- At the time of writing, Buzz had a **compact API** and fewer restrictions (no rate limiting), facilitating data mining.
- Understanding Buzz can be enhanced by exploring a **public feed** or using the Buzz link in Gmail:
 - Public feeds are accessible via a URL format:

4. Buzz API Structure :

- The Buzz API is **RESTful** and includes three main resources:
 - **People**
 - **Activities** (similar to posts)
 - **Comments**
- Buzz activities are considered **text-based resources** but also integrate rich media like photos and videos.

5. Further Learning :

- The Google Buzz API documentation provides a good overview for casual users.
- For more in-depth understanding of **RESTful services** , consider reading **RESTful Web Services** (O'Reilly), which includes practical examples.

This chapter sets the stage for exploring data mining techniques using Google Buzz, emphasizing the integration of text mining fundamentals and API utilization.

Integrating Twitter with Google Buzz

1. Gmail Account Settings :

- Users can customize their **Gmail settings** to integrate activity from **Twitter** and other services directly into their **Buzz feed** .
- This feature enhances the user experience by consolidating social media activities.

2. Buzz as a Hybrid Platform :

- Google Buzz acts as a combination of **Twitter** and **blogs** , blending the immediacy of tweets with the more extended content typical of blog posts.
- This hybrid nature makes Buzz suitable for various types of communication and content sharing.

3. User Experience :

- The integration allows users to follow updates from multiple platforms without needing to switch between apps or services.
- This seamless interaction fosters a richer social networking experience.

In summary, the ability to merge Twitter activity into Google Buzz enhances user engagement and showcases Buzz as a versatile social platform.

Fetching and Processing Google Buzz Data

1. Buzz Python Client :

- A **Python-based client** called **buzz** is available for interacting with Google Buzz. You can install it using `easy_install buzz-python-client`.
- More information can be found at: `buzz-python-client`.

2. Accessing Public Data :

- We will fetch data from **Tim O'Reilly's public Buzz feed**. For this example, we won't need **OAuth authentication** since we're accessing public information.
- Focus is on mining **free-text data** from posts, rather than exploring social relationships through friend/follower data.

3. Data Structure :

- Buzz data is retrieved as a **feed** that may contain **markup** and **escaped HTML entities**.
- Example 7-1 demonstrates how to create a structured format for each Buzz post, including its **title**, **content**, **comments**, and **link**.

4. Cleaning Data :

- The **cleanHtml function** is essential for processing the fetched data. It removes HTML markup and converts escaped entities to ensure the content is clean and readable.
- This step is critical because analysis routines may not handle HTML properly.

5. Storage Considerations :

- Although the example initially uses **CouchDB** for data storage, the chapter will shift to using **pickling** for simplicity, focusing on text-mining techniques instead of storage methods.
- For those interested in using CouchDB more extensively, previous chapters provide insights into that approach.

Example Code Overview

- The provided Python code snippet demonstrates the process of fetching and cleaning Buzz data for text mining. Key libraries used include:
 - **buzz** : To interact with Google Buzz.
 - **BeautifulSoup** : For parsing HTML.
 - **nlTK** : For natural language processing.

In summary, this section outlines how to efficiently collect and clean data from Google Buzz, preparing it for text mining and analysis.

1. Setting Up the Client :

- Use the **buzz.Client()** to connect to the Google Buzz API.
- The **posts data** variable fetches public posts from a specified user, limited by **max results** .

2. Processing Posts :

- Initialize an empty list called **posts** to store processed data.
- For each post in **posts data** :
 - Retrieve **comments** associated with the post, extracting the commenter's name and cleaned content.
 - The **link** to the post is also captured.
 - Create a dictionary for each post containing:
 - **title** : Cleaned title of the post.
 - **content** : Cleaned content of the post.
 - **comments** : List of cleaned comments.
 - **link** : URI of the post.
 - Append the post dictionary to the **posts** list.

3. Storing Data :

- Check if the output directory '**out**' exists; if not, create it.
- Save the **posts** list as a JSON file in the '**out**' directory, named after the user (USER).
- Optionally, you can store the data in **CouchDB** . If using CouchDB:
 - Connect to the server and create a new database named after the user.
 - Update the database with the posts data.

Next Steps: Data Analysis with NLTK

- **NLTK (Natural Language Toolkit)** is a powerful library for exploring and analyzing textual data.
- It's designed for easy data exploration and allows for quick insights without requiring extensive setup.
- Before proceeding, it's beneficial to follow an interpreter session (referenced as **Example 7-2**) to understand some of the built-in functionalities of NLTK.

In summary, this section outlines how to fetch, process, and store Google Buzz posts and comments while setting the stage for text analysis using NLTK.

Using NLTK for Text Analysis

1. Getting Help with NLTK :

- Use the built-in **help()** function to access documentation. For example, running **help(nltk)** provides details about the NLTK library.
- Not all functionalities from the interpreter are suitable for production. Some methods, like **nltk.text.concordance** , are more for demonstration purposes and output to standard output rather than returning data structures.

2. Demo Functionality :

- Many NLTK modules have demo functions to showcase their capabilities. For instance, running `nltk.text.demo()` can give insights into the features of the `nltk.text` module.
- The source code for these demos serves as a useful starting point for learning how to utilize new APIs.

3. Tokenization :

- The examples in this chapter use the `split()` method for basic tokenization, which separates text into words.
- Chapter 8 will cover more advanced tokenization techniques that might be more effective.

Example Session: Analyzing Buzz Data with NLTK

- After generating a **USER.buzz** file, the following steps illustrate how to analyze the data:

1. Import Necessary Libraries :

```
python Copy code import nltk import json
```

2. Load Buzz Data :

- Read the JSON data from the **USER.buzz** file.

```
python Copy code buzz_data = json.loads( open ( "out/timoreilly.buzz" ).read())
```

3. Combine All Content :

- Concatenate the content of all posts into a single string.

```
python Copy code all_content = " ".join([p[ 'content' ] for p in buzz_data ])
```

4. Count Characters :

- Use `len(all_content)` to determine the total character count of the combined content (e.g., 42,930 characters).

5. Tokenization :

- Split the combined content into tokens (individual words).

```
python Copy code tokens = all_content.split()
```

6. Creating NLTK Text Object :

- Use the tokens to create an NLTK Text object for further analysis.

```
python Copy code text = nltk.Text(tokens)
```

7. Finding Concordances :

- Use the **concordance** method to find instances of a specific term, such as "open".

```
python Copy code text.concordance( "open" )
```

This displays all occurrences of the word "open" within the text, providing context for each instance.

Summary

This section introduces the basic usage of NLTK for text analysis, highlighting how to get help, use demo functionalities, and perform tokenization. An example session demonstrates loading, processing, and analyzing data from Google Buzz using NLTK tools, emphasizing practical applications in text mining.

Analyzing Text Data with NLTK: Key Concepts and Techniques

1. Collocations :

- Use **text.collocations()** to find common word pairs that frequently appear together. Example results might include:
 - **open source**
 - **Web 2.0**
 - **free software**
- This helps identify key phrases within the text.

2. Vocabulary Index :

- Create a **vocabulary index** using **text.vocab()** to understand the frequency of words.
- Example outputs for specific terms:
 - **"open"** : 19 occurrences
 - **"source"** : 14 occurrences
 - **"web"** : 3 occurrences
- The total number of tokens (words) is **6,942** , and there are **2,750 unique tokens** .

3. Filtering Stopwords :

- Generate a list of the most common words, excluding common stopwords (like "the", "and", "is").
- Example filtered words include:
 - **open , source , Apple , Google , innovation .**

4. Long Words and URLs :

- Identify long words (more than 15 characters) that do not start with "http":
 - Examples include **interoperability** and **entrepreneur-friendly** .
- Count the number of URLs in the text, with **35 URLs** found.

5. Word Frequency Ranking :

- Enumerate words by their frequency:
 - **1st** : "the" - 317 times
 - **2nd** : "to" - 199 times
 - **3rd** : "of" - 180 times
- This helps visualize which words dominate the text.

Summary

This section illustrates how to analyze text data using NLTK by identifying collocations , building a vocabulary index , filtering out stopwords , and counting specific characteristics of the text, like long words and URLs . Additionally, it shows how to rank word frequencies, providing insight into the text's main themes and concepts.

1. Downloading NLTK Data :

- To use **stopwords** in NLTK, run the command: `python Copy code nltk.download('stopwords')`
- For a complete installation of NLTK data, it's better to execute: `python Copy code nltk.download()`

2. Frequency Distribution :

- The last command in the interpreter session shows words sorted by frequency.
- Common words, known as **stopwords** (like **"the," "to,"** and **"of"**), appear most frequently.
- There is a **steep decline** in frequency after these common words, resulting in a long tail of less frequent terms.

3. Zipf's Law :

- **Zipf's Law** states that a word's frequency is inversely proportional to its rank in a frequency list.
- For example:
 - If the most frequent word accounts for **N%** of total words, the second accounts for **(N/2)%** , the third for **(N/3)%** , and so on.
- This creates a distribution that, when graphed, shows a curve hugging each axis.

4. Distribution Characteristics :

- Most of the area in the frequency distribution lies in its **tail** , which tends to be quite long for larger corpora.
- If plotted on a logarithmic scale, the distribution curve will approach a **straight line** for sufficiently large sample sizes.

Summary

In summary, understanding word frequency analysis using NLTK involves downloading necessary data, observing the frequency distribution of terms, and applying Zipf's Law to grasp how word occurrences relate to their ranks. The resulting distribution characteristics emphasize the prevalence of a small number of common words, while a long tail indicates a wide variety of less frequent words.

Understanding Zipf's Law and Text Mining Fundamentals

1. Zipf's Law :

- **Insight** : Zipf's Law describes how word frequency distributions in a corpus behave.
- **Estimation** : If you have **1 million** non-unique words, and the most frequent word (often **"the"**) makes up **7%** of the total, you can estimate calculations an algorithm may perform when analyzing a subset of terms.
- **Practical Use** : Simple calculations can help validate assumptions about processing time and confirm the feasibility of computations on large datasets.

2. Text Mining Fundamentals :

- While advanced **Natural Language Processing (NLP)** techniques (like sentence segmentation, tokenization, and entity detection) are crucial for deep understanding, starting with basic principles from **Information Retrieval (IR)** is beneficial.
- This chapter covers foundational concepts such as **TF-IDF** , **cosine similarity** , and **collocation detection** . Chapter 8 will delve deeper into NLP techniques.

3. Introduction to TF-IDF :

- **Definition** : TF-IDF stands for **Term Frequency-Inverse Document Frequency** . It's a key method for retrieving relevant documents from a corpus.
- **Purpose** : TF-IDF calculates scores that indicate the relative importance of terms in documents.
- **Formula** : $tf_idf = tf \times idf$ $\text{tf_idf} = \text{tf} \times \text{idf}$ $tf_idf = tf \times idf$
 - **Term Frequency (TF)** : Measures how important a term is within a specific document.
 - **Inverse Document Frequency (IDF)** : Measures the importance of a term across the entire corpus.
- **Usage** : The resulting score helps in retrieving documents based on the relevance of the terms, and it has been widely used in search engines.

Summary

In summary, understanding Zipf's Law provides insights into word frequency distributions, helping to estimate computational requirements. Basic text mining principles, especially TF-IDF, lay the groundwork for effective information retrieval, making them essential for analyzing and querying text data.

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Understanding Term Frequency in a Sample Corpus

1. Sample Corpus :

- **Definition** : A corpus is a collection of documents used for text analysis.
- **Example** : python Copy code

```
corpus = { 'a' : "Mr. Green killed Colonel Mustard in the study with the candlestick. Mr. Green is not a very nice fellow." , 'b' : "Professor Plumb has a green plant in his study." , 'c' : "Miss Scarlett watered Professor Plumb's green plant while he was away from his office last week." }
```
- **Term Extraction** : Each document's text is split into lowercase terms: python Copy code

```
terms = { 'a' : [ i.lower() for i in corpus[ 'a' ].split() ], 'b' : [ i.lower() for i in corpus[ 'b' ].split() ], 'c' : [ i.lower() for i in corpus[ 'c' ].split() ] }
```

2. Calculating Term Frequency (TF) :

- **Basic Definition** : Term frequency is the number of times a term appears in a document.
- **Normalization** : To account for document length, term frequency is often normalized by dividing by the total number of terms in the document.
 - Example:
 - In `corpus['a']` , "green" occurs **2 times** out of **19** total terms: $TF = \frac{2}{19}$ $TF = \frac{2}{19}$
 - In `corpus['b']` , "green" occurs **1 time** out of **9** total terms: $TF = \frac{1}{9}$ $TF = \frac{1}{9}$
 - **Result** : Despite higher raw frequency in `corpus['a']` , `corpus['b']` has a higher normalized frequency for "green".

3. Cumulative Scoring for Compound Queries :

- When querying for compound terms (e.g., "Mr. Green"), the **cumulative term frequency** is calculated by summing the individual term frequencies for each document.
- **Example Scores** :

Document	tf(Mr.)	tf(Green)	Sum
corpus['a']	2/19	2/19	4/19 (0.2105)

	Document	tf(Mr.)	tf(Green)	Sum
corpus['b']	0	1/9	1/9	0.1111
corpus['c']	0	1/16	1/16	0.0625

4. Analysis of Results :

- The results show that **corpus['a']** scores highest due to the presence of both terms in the compound query "Mr. Green".
- **Potential Issues** : While this method works well in this simple example, it may present challenges in more complex datasets, such as dealing with variations in term frequency across different contexts or documents.

Summary

In summary, understanding term frequency and its normalization is crucial for evaluating document relevance. By analyzing a small corpus, we can see how term frequency calculations inform the ranking of documents based on their content. This foundational concept is key to more advanced text mining techniques.

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Understanding Term Frequency Limitations and Inverse Document Frequency

1. Document Representation :

- **Concept** : Documents are treated as **unordered collections of words** . For example, queries like "Green Mr." or "Mr. Green" yield the same scores, even if certain phrases don't exist in the text.
- **Issue** : This approach can lead to poor results because it ignores punctuation and context around terms.

2. Limitations of Term Frequency :

- **Equal Weighting Problem** : Term frequency (TF) treats all terms equally, regardless of their actual importance. Frequent words (stopwords) can skew results.
- **Example** : In the phrase "the green plant":
 - **Corpus['a']** : "the" appears twice, inflating its score.
 - **Corpus['c']** : "green" and "plant" appear once each, leading to a lower score.
- **Scores Breakdown** (for "the green plant"):

	Document	tf(the)	tf(green)	tf(plant)	Sum
corpus['a']	2/19	2/19	0	4/19	0.2105
corpus['b']	0	1/9	1/9	2/9	0.2222
corpus['c']	0	1/16	1/16	1/8	0.125

- **Result** : **Corpus['a']** is wrongly ranked higher than **corpus['c']** , despite intuition suggesting otherwise.

3. Stopwords :

- **Definition** : Commonly used words (e.g., "the", "and") that can distort relevance scoring.
- **Solution** : Toolkits like **NLTK** provide stopwords lists to filter out these terms.

4. Inverse Document Frequency (IDF) :

- **Purpose** : IDF is a normalization metric that addresses the limitations of term frequency by considering the total number of documents containing a term.
- **Intuition** : Terms that are less common across documents receive higher scores. This helps counterbalance the influence of stopwords.

- **Example** : A query for "green" will have a lower IDF score than "candlestick" because "green" appears in every document, while "candlestick" only appears in one.
- **Calculation** : IDF uses a logarithm to compress the score range, which makes it more manageable for later calculations with TF.

Summary

In summary, while term frequency provides initial insights, it has limitations due to equal weighting and the presence of stopwords. Inverse document frequency serves as a corrective measure, enhancing relevance scoring by considering the rarity of terms across a corpus. This combination allows for more accurate document ranking in text mining applications.

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Understanding TF-IDF Calculation

1. TF-IDF Overview :

- **Definition** : TF-IDF stands for **Term Frequency-Inverse Document Frequency** . It combines two factors:
 - **Term Frequency (TF)** : How often a term appears in a document.
 - **Inverse Document Frequency (IDF)** : How unique or rare a term is across the entire corpus.
- **Formula** : The overall score is computed as **tf-idf = tf * idf** .

2. Logarithmic Compression :

- **Purpose** : The logarithm compresses a wide range of values into a smaller, more manageable scale. This helps to mitigate the impact of extreme values and makes the scoring system more effective.

3. Implementation Example :

- **Code Overview** : Example 7-4 provides a basic implementation of the TF-IDF calculation. Here's a simplified outline: `python Copy code`

```
# Import necessary libraries
import sys
from math import log

# Capture query terms from command line arguments
QUERY, TERMS = sys.argv[1:]

# Define function to calculate term frequency
def tf ( term, doc, normalize= True ):
    # Normalize the document to lowercase and split into words
    doc = doc.lower().split()
    if normalize:
        # Return normalized term frequency
        return doc.count(term.lower()) / float ( len (doc))
    else :
        # Return raw count (not normalized)
        return doc.count(term.lower())
```

4. Key Concepts :

- **Normalization** : Normalizing term frequency helps account for different document lengths, ensuring a fair comparison.
- **Document Uniqueness** : IDF emphasizes terms that are less common across documents, enhancing the relevance of results.

Summary

This framework allows for a nuanced scoring system that considers both the frequency of terms within individual documents and their uniqueness across a corpus. By leveraging TF-IDF, one can effectively rank documents in

TF-IDF Implementation Notes

1. Functions Overview :

◦ Term Frequency (TF) :

- Function: `tf(term, doc, normalize=True)`
- Purpose: Calculates how frequently a term appears in a document.
- Returns normalized frequency: python Copy code `return doc.count(term.lower()) / 1.0`

◦ Inverse Document Frequency (IDF) :

- Function: `idf(term, corpus)`
- Purpose: Measures how unique a term is across the corpus.
- Calculation:
 - Counts how many documents contain the term.
 - Uses logarithm to adjust scores, ensuring the value is greater than 1 for consistent scoring:
python Copy code `return 1.0 + log(float (len (corpus)) / num texts_with_term)`
 - Handles cases where a term does not appear in any documents with a **try-except** block to avoid division by zero.

◦ TF-IDF Score :

- Function: `tf_idf (term, doc, corpus)`
- Purpose: Combines TF and IDF to provide a score that reflects both term frequency and uniqueness.
- Calculation: python Copy code `return tf(term, doc) * idf(term, corpus)`

2. Corpus Definition :

- A sample corpus contains three documents: python Copy code `corpus = { 'a' : 'Mr. Green killed Colonel Mustard in the study with the candlestick.' , 'b' : 'Professor Plumb has a green plant in his study.' , 'c' : 'Miss Scarlett watered Professor Plumb's green plant while he was away.' }`

3. Scoring Queries :

- The script initializes a dictionary to store cumulative TF-IDF scores for each document.
- For each term in the query, it:
 - Calculates TF for each document.
 - Calculates IDF for the term across the corpus.
 - Computes the TF-IDF score for each document and updates the cumulative scores.
- The final scores for the query are printed.

4. Sample Queries :

- The script processes queries with terms such as:
 - "green"
 - "Mr. Green"
 - "the green plant"

This implementation demonstrates how to compute TF-IDF scores for documents in a corpus. By understanding the importance of term frequency and document uniqueness, users can effectively rank documents based on their relevance to specific queries. Although this example uses a small dataset, the principles apply to larger text corpora.

Understanding TF-IDF Calculations

1. IDF Calculations :

- **Inverse Document Frequency (IDF)** is calculated for terms across the entire corpus but displayed per document. This allows for easy verification of **TF-IDF scores** by checking individual rows.
- **TF-IDF** is powerful, even though it does not consider **word proximity** or **ordering** within documents.

2. Tables Overview :

- **Table 7-3** presents the individual calculations of **term frequency (TF)** and **inverse document frequency (IDF)** for three documents (corpus['a'], corpus['b'], corpus['c']) and various terms.
- **TF Values** for each document:
 - `tf(mr.)` , `tf(green)` , `tf(the)` , `tf(plant)` show how often each term appears in the documents.
- **IDF Values** for each term are consistent across documents, indicating how common or rare each term is in the corpus.

3. Summed TF-IDF Values :

- **Table 7-4** displays the summed **TF-IDF values** for sample queries: "green," "Mr. Green," and "the green plant."
- Each document's score is calculated by summing the TF-IDF values of the relevant terms:
 - For "green," corpus['b'] scores highest due to its shorter length, giving it a normalized advantage.
 - For "Mr. Green," corpus['a'] has a higher score because it contains both terms.
 - The query "the green plant" illustrates how multiple terms contribute to the score, with corpus['b'] again performing well.

4. Qualitative Analysis :

- The results align with expectations:
 - **Corpus['b']** is the top document for the query "green," despite "green" appearing more times in corpus['a'] because of the shorter document length.
 - The **IDF's** impact is neutral since "green" is found in all documents.

Conclusion

The analysis demonstrates how TF-IDF effectively ranks document relevance based on term frequency and uniqueness. This methodology provides a systematic approach to evaluating text data, even in its simplistic form, without considering the order of words.

Understanding IDF Adjustments in TF-IDF Calculations

1. IDF Score Considerations :

- If **Inverse Document Frequency (IDF)** scores are calculated to be **0.0** for terms like “green” appearing in all documents, this might be appropriate. For example, in a corpus of 100,000 documents where “green” appears in all, it would likely be treated as a **stopword** , and its effects should be eliminated from queries.

2. Adjustment in IDF Calculations :

- The sample implementation adds **1.0** to the logarithmic IDF calculation. This adjustment ensures that IDF scores remain above **1.0** , preventing situations where the function could return values less than **1.0** .
- If IDF returns a value less than **1.0** , multiplying two fractions in the **TF-IDF** calculation could result in a score smaller than either term, which is an issue since we want higher scores for more relevant queries.

Applying TF-IDF to Buzz Data

1. Using NLTK for Querying :

- The **Natural Language Toolkit (NLTK)** provides tools to simplify the application of TF-IDF to text data. This allows users to query data without building everything from scratch.
- The example provided (Example 7-5) shows how to load Buzz data from a **JSON** file and query it using multiple terms for relevance scoring.

2. Example Implementation :

- The code reads Buzz data, splits the content into lowercase words, and utilizes NLTK’s **TextCollection** to manage term frequency and IDF calculations.
- The resulting relevant posts are determined by scoring based on the query terms provided.

Conclusion

Understanding the nuances of IDF adjustments and leveraging NLTK can enhance the effectiveness of TF-IDF in querying large datasets like Buzz data. The adjustments help ensure that the calculations yield meaningful scores, reflecting the relevance of terms in documents.

Querying Buzz Data with TF-IDF

1. Scoring Documents :

- Initialize a score at **0** for each document.
- For each **query term** (converted to lowercase), calculate its **TF-IDF score** against the current document using `tc.tfidf_idf()`, and add this score to the total.

2. Storing Relevant Posts :

- If the score for a document is greater than **0**, append a dictionary containing the score, title, and link of the post to the **relevant posts** list.

3. Sorting and Displaying Results :

- Sort **relevant posts** by score in **descending order**.
- Print the title, link, and score for each relevant post.

4. Sample Output :

- For the query "gov 2.0" on Tim O'Reilly's Buzz posts, example results include:
 - Title: "Flattered but somewhat bemused..."
 - Link: [Link](#)
 - Score: **0.02245**
 - Other results follow a similar format, showing the effectiveness of the **TF-IDF** metric in ranking posts by relevance.

5. Evaluating Results :

- Although the absolute score values are not crucial, their relative differences allow for effective document sorting based on relevance. Experiment with different queries to see how well the system identifies relevant documents.

6. Potential Improvements :

- Consider techniques like **stemming** to reduce variations in word forms (e.g., different tenses) to enhance similarity calculations. The `nltk.stem` module offers implementations for common stemming algorithms.

Finding Similar Documents

1. Cosine Similarity :

- After identifying relevant documents, you may want to find other documents similar to those of interest.
- **Cosine similarity** is a common method for comparing the content of documents, helping to uncover relationships and similarities between them.

Summary

The use of TF-IDF allows effective querying of text data by scoring and ranking documents based on their relevance to specified search terms. Enhancements, such as stemming and exploring cosine similarity, can further refine the results and improve the overall querying process.

1. Introduction to Vector Space Models :

- Vector space models provide a way to represent documents as **vectors** in a **multidimensional space** .
- Each document is represented as a vector, and the **distance** between vectors indicates the **similarity** between the corresponding documents.

2. Query Representation :

- A **query** can also be represented as a vector. By measuring the distance between the query vector and document vectors, the most relevant documents can be identified.

3. Importance of Understanding Vectors :

- Grasping vector space models is crucial for anyone interested in **text mining** or **information retrieval (IR)** .
- If you're not interested in the theoretical background, you can skip to the implementation details.

4. What is a Vector? :

- A **vector** is a list of numbers that indicates both a **direction** and a **magnitude** from an origin point in space.
- Vectors can be visualized as line segments from the origin to a point in an **N-dimensional space** .

5. Example of a Vector :

- For a document defined by two terms, such as "Open" and "Web", it could have a corresponding vector represented as (0.45, 0.67). Here, the values represent the **weight** or significance of each term in the document.

Summary

Vector space models enable the representation of documents and queries as vectors in a multidimensional space, facilitating the measurement of document similarity through distance metrics. Understanding these concepts is essential for effective text mining and information retrieval.

Representing Documents as Vectors

1. Document Representation in Vector Space :

- A document can be represented as a **vector** in a **vector space** , with each dimension corresponding to a term's **TF-IDF score** .
- In a 2D space, a vector might extend from the origin (0,0) to a point like (0.45, 0.67), where:
 - **X-axis** represents the term "Open"
 - **Y-axis** represents the term "Web"

2. Higher Dimensions :

- While visualizing documents with only a few terms is straightforward, real-world documents often contain **hundreds of terms** .
- The same principles apply in **higher-dimensional spaces** (e.g., 3D, 10D, or even 367D), although it's harder to visualize.
- For instance, adding a third term like "Government" would create a vector in 3D space.

3. Vector Operations :

- Mathematical operations applicable in 2D can also be extended to higher dimensions without any loss of

functionality.

4. Cosine Similarity :

- To measure the **similarity** between two document vectors, **cosine similarity** is used. This metric is calculated based on the **cosine of the angle** between the two vectors.
- **Cosine similarity** is an effective way to compare documents represented as term vectors, supported by extensive scientific research.

5. Limitations :

- While cosine similarity is powerful, it shares some limitations with the TF-IDF method. Understanding these limitations is essential for building effective search engines and information retrieval systems.

Summary

Documents can be effectively represented as vectors in a multidimensional space using their TF-IDF scores. Cosine similarity serves as a robust metric for comparing these document vectors, allowing for the measurement of similarity despite challenges in visualizing higher dimensions.

Understanding Cosine Similarity

1. Cosine Similarity Basics :

- **Cosine similarity** measures the similarity between two vectors based on the **cosine of the angle** between them.
- This metric is equivalent to the **dot product** of the unit vectors derived from the original vectors.

2. Intuition Behind Cosine Similarity :

- **Closer Vectors** : The smaller the angle between two vectors, the larger the cosine value, indicating higher similarity.
- **Identical Vectors** : Two identical vectors have an angle of **0 degrees** and a similarity score of **1.0** .
- **Orthogonal Vectors** : Vectors at a **90-degree angle** have a similarity score of **0.0** .

3. Unit Vectors :

- A **unit vector** has a length of **1.0** and normalizes the variations in vector lengths, making similarity calculations more robust.

Clustering Posts Using Cosine Similarity

1. Calculating Document Similarity :

- To compute the similarity between two documents, create a **term vector** for each and calculate the **dot product** of their unit vectors.
- The **NLTK library** provides the function `nltk.cluster.util.cosine_distance(v1, v2)` to facilitate this calculation.

2. Creating Term Vectors :

- Each document's term vector is formed by assigning **TF-IDF scores** to its terms.
- When documents have different vocabularies, **placeholders** (0.0) are used in the vectors for missing terms. This ensures both vectors are of the same length and order.

3. Example :

- If **Document 1** has terms (A, B, C) with TF-IDF weights (0.10, 0.15, 0.12) and **Document 2** has terms (C, D, E) with weights (0.05, 0.10, 0.09), the vectors would be adjusted to maintain the same length and allow for cosine similarity calculations.

Summary

Cosine similarity is a crucial metric for comparing document vectors, reflecting their relative orientation in space. By using term vectors and normalizing them through unit vectors, we can effectively measure the similarity between documents, facilitating tasks like clustering and retrieval.

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Finding Similar Documents Using Cosine Similarity

1. Creating Document Vectors :

- For **Document 1** , the derived vector might be **(0.10, 0.15, 0.12, 0.0, 0.0)** .
- For **Document 2** , the derived vector could be **(0.0, 0.0, 0.05, 0.10, 0.09)** .
- These vectors can be input into NLTK's `cosine_distance` function to calculate cosine similarity.

2. Cosine Distance Function :

- The `cosine_distance` function utilizes the **numpy** module to efficiently compute the **dot product** of the unit vectors, resulting in the cosine similarity value.
- While TF-IDF scores are often used for this purpose, any relevant scoring metric could be applied.

3. Example Implementation :

- **Example 7-7** demonstrates how to use cosine similarity to identify the most similar document for each document in a Buzz data corpus. This approach can also be applied to other unstructured data types like blog posts and books.

Code Breakdown for Finding Similar Documents

1. Data Loading :

- The code begins by loading textual data from a specified source (JSON format).
- Each post's content is split into lowercase words to prepare for analysis.

2. Term-Document Matrix :

- A **term-document matrix** is created, where `td_matrix[doc_title][term]` holds the TF-IDF score

for a term in a specific document.

- The frequency distribution (`fdist`) of each post is calculated to generate TF-IDF scores for the terms.

3. Building Vectors :

- The vectors for each document are structured so that term scores occupy the same positions in all vectors, facilitating similarity calculations.

4. Calculating Distances :

- A **distances dictionary** is initialized to store similarity scores between each document pair based on their vectors.

Summary

The process of finding similar documents using cosine similarity involves creating term vectors for each document, computing their cosine similarity through efficient mathematical operations, and organizing the results for easy retrieval. This method is versatile and applicable to various forms of unstructured text data.

Finding the Most Similar Documents

1. Initialization :

- Set initial values: `max_score` to **0.0** and `most_similar` to **(None, None)** . This will store the highest similarity score and the corresponding document.

2. Iterate Over Documents :

- For each document in the term-document matrix (`td_matrix`), copy the term scores for both the current document and the one being compared.

3. Fill Gaps :

- Ensure both term maps (from the two documents) have the same dimensions:
 - If a term from `terms1` is not in `terms2` , add it with a score of **0** .
 - Conversely, do the same for terms in `terms2` not found in `terms1` .

4. Create Vectors :

- Construct vectors (**v1 and v2**) from the term maps. Sort the items to ensure consistent ordering.

5. Compute Similarity :

- Use **cosine distance** to calculate the similarity between the two document vectors:
 - Store the result in the `distances` dictionary.
- If comparing the same document (i.e., `link1 == link2`), skip to the next iteration.

6. Update Maximum Score :

- If the calculated distance is greater than `max_score` , update both `max_score` and `most_similar` with the current document's title and link.

7. Output Results :

- Print the most similar document's title, link, and score.

Application of Cosine Similarity

- **Querying as Document Comparison :**
 - When querying a vector space, the same method used for finding document similarity applies. Instead of comparing just document vectors, compare a **query vector** against document vectors.
- **Scalability Considerations :**
 - Directly comparing a query vector to all document vectors in a large corpus is inefficient. To manage larger datasets, implement appropriate indexing strategies for better performance.

Summary

This process efficiently identifies the most similar documents by comparing their term vectors using cosine similarity. Additionally, understanding how to construct and compare query vectors is crucial for scalable information retrieval systems.

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Visualizing Similarity with Graph Structures

1. Overview :

- There are various methods to visualize similarity between items. This section focuses on using **graph-like structures**, where links between documents represent their similarity.

2. Using Protovis :

- **Protovis** is an HTML5-based visualization toolkit developed by the Stanford Visualization Group. It is tailored for data scientists and balances high-level and low-level interfaces.
- Minimal changes to previous examples can generate nodes (documents) and edges (similarity links) for visualization.

3. Creating Visualizations :

- A **nested loop** calculates similarities based on the Buzz data, establishing links based on a statistical threshold.
- The resulting visualizations include:
 - **Arc Diagram (Figure 7-6) :**
 - Displays arcs between nodes that have similarity links.
 - Node sizes reflect their connection degree (number of links).
 - Nodes are sorted to reduce clutter, making it easier to identify highly connected nodes.
 - Titles are shown vertically, and tooltips provide titles on hover. Clicking a node opens the corresponding Buzz activity.

4. Matrix Diagram (Figure 7-7) :

- Represents similarity scores with color intensity; darker cells indicate higher similarity.
- The diagonal is omitted to prevent focus on self-similarities (perfect scores).
- Tooltips show similarity scores when hovering over cells.
- **Advantages** : No overlapping edges, making it cleaner and easier to interpret.

- **Disadvantages** : Arc diagrams can complicate pathfinding, but this is less critical in this context.

5. Choosing Visualization Types :

- Both arc and matrix diagrams have their merits. The choice depends on personal preference and the specific data being visualized. Additional enhancements like event handlers and color coding can be implemented for further clarity and interaction.

Summary

Using graph structures and tools like Protovis allows for effective visualization of document similarities. Both arc and matrix diagrams offer unique advantages, enabling users to explore relationships between items clearly.

Protovis Visualizations of Buzz Activities

1. Matrix Diagram (Figure 7-7) :

- **Purpose** : Displays the relationships between Buzz activities using a grid format.
- **Color Intensity** : Each cell's color represents the strength of similarity; darker colors indicate **higher similarity** between activities.
- **Diagonal Omission** : The diagonal (self-similarities) is removed to avoid distraction, focusing attention on inter-document relationships.
- **Tooltips** : Hovering over a cell reveals the exact similarity score.

2. Arc Diagram (Figure 7-6) :

- **Purpose** : Visualizes the linkages between Buzz activities with arcs connecting nodes (activities).
- **Node Sizing** : The size of each node reflects its number of connections, helping identify key activities at a glance.
- **Sorting and Clutter Reduction** : Nodes are arranged to minimize visual clutter, making connections clear.
- **Interactivity** : Titles can be viewed by hovering, and clicking a node redirects to the related Buzz activity.

Summary

Both diagrams provide valuable insights into the relationships between Buzz activities, with the matrix diagram focusing on similarity scores and the arc diagram emphasizing connectivity and interactivity. These visualizations enhance the understanding of how different activities relate to each other within the dataset.

Understanding Bigrams in Text Processing

1. Importance of Bigrams :

- **Definition** : A **bigram** is a sequence of two consecutive tokens (words) in a text.
- **Contextual Meaning** : Analyzing bigrams provides insight into phrases, capturing meaning that single words may not convey. For instance, the words "open" and "government" could imply "open government" rather than just standalone meanings.

2. N-grams Overview :

- **General Concept** : An **n-gram** is a representation of all possible consecutive sequences of **n** tokens. For bigrams ($n=2$), if you have a sequence like ["Mr.", "Green", "killed", "Colonel", "Mustard"], the bigrams are:
 - [("Mr.", "Green"), ("Green", "killed"), ("killed", "Colonel"), ("Colonel", "Mustard")].

3. Storage Considerations :

- The storage needed for n-grams can be estimated as $(T-1) * n$, where **T** is the total number of tokens.
- For example:
 - A document with **1,000 tokens** that requires **8 KB** of storage would need about **16 KB** for bigrams and **24 KB** for trigrams.

4. Statistical Analysis of Bigrams :

- To identify meaningful phrases (collocations), bigrams must be statistically analyzed. This involves determining which bigrams frequently occur together in a larger text sample.

5. Patterns and Clustering :

- Bigrams help in clustering words that commonly appear together, revealing patterns such as proper names ("Mr. Green") or common phrases ("open source").
- Analyzing bigrams can lead to discovering significant phrases without requiring extensive additional analysis.

Summary

Bigrams are a powerful tool in text processing that helps capture the meaning of phrases, allowing for deeper insights into the text. By analyzing the relationships between pairs of words, we can identify collocations and meaningful patterns that inform understanding of the content. However, this comes with increased storage requirements, which must be considered in practical applications.

Exploring Bigrams, Trigrams, and N-grams in Text Analysis

1. Emergence of Patterns :

- Analyzing **trigrams** (3-grams) and larger n-grams can reveal patterns in text. **N-grams** provide insight into word sequences that occur frequently, enhancing the understanding of text context.

2. Comparison with Collocations :

- Computing bigrams can yield similar results to using the **collocations** function in NLTK. However, bigram analysis incorporates additional statistical assessments, particularly regarding rare words.

3. NLTK for N-grams :

- **NLTK** (Natural Language Toolkit) simplifies the process of computing n-grams and discovering collocations from text. It allows users to analyze the context in which tokens (words) appear.
- Example of bigram computation using NLTK: python Copy code

```
import nltk
nltk.ngrams( "Mr. Green killed Colonel Mustard in the study with the candlestick." .split(), 2 )
```

 This produces: css Copy code

```
[ ( 'Mr.' , 'Green' ), ( 'Green' , 'killed' ), ( 'killed' , 'Colonel' ), ...]
```

4. Collocations Example :

- To identify collocations (frequently occurring pairs), you can use: python Copy code

```
txt = nltk.Text( "Mr. Green killed Colonel Mustard..." .split())
txt.collocations()
```
- This will output common phrases, such as "Mr. Green".

5. Limitations of Built-in Functions :

- Built-in functions like `nltk.Text.collocations` don't provide manipulable data structures. Users may need to adapt the source code for custom applications.

6. Custom Collocations Computation :

- Example code for computing collocations while retaining control over the output: python Copy code

```
import sys
import json
import nltk
BUZZ_DATA = sys.argv[ 1 ]
buzz_data = json.loads( open( BUZZ_DATA ).read() )
all_tokens = [token for post in buzz_data for token in post[ 'content' ].lower().split()]
finder = nltk.BigramCollocationFinder.from_words( all_tokens )
```
- This script processes a dataset to find bigrams and allows further manipulation of the results.

Summary

Bigrams and n-grams are essential for text analysis, helping uncover patterns and collocations that improve comprehension. NLTK provides efficient tools for these tasks, although users may need to customize their approaches for specific needs.

Analyzing Bigrams with NLTK: A Step-by-Step Guide

1. Filtering Bigrams :

- Use `finder.apply_freq_filter(2)` to **exclude** bigrams that appear less than twice in the dataset. This ensures that only significant pairs are analyzed.
- Apply a **word filter** using `finder.apply_word_filter(lambda w: w in nltk.corpus.stopwords.words('english'))` to remove common **stopwords** (e.g., "the", "is") from the bigram analysis.

2. Scoring Bigrams :

- The **scoring metric** employed is the **Jaccard Index**, which measures the similarity between sets. Here, it evaluates the co-occurrence of terms in bigrams compared to other possible words.

- The Jaccard Index is defined in `nlk.metrics.BigramAssocMeasures.jaccard` . It uses a **contingency table** to assess the relationships between terms in the bigram.

3. Ranking Bigrams :

- The code retrieves the best bigrams using `finder.nbest(scorer, N)` , where **N** specifies how many top bigrams to return based on their scores.

4. Output of Bigrams :

- The resulting bigrams are printed, showing pairs of words that frequently appear together, providing **context** and **meaning** beyond individual tokens.

5. Example Output :

- The following is a sample output of scored bigrams, illustrating the contextual significance:

```
sql Copy code
annalee saxenian nexus one cafe standards certainly true eric schmidt olive oil open source 1
/ 4 cup free software andy rubin front page mr. o'reilly o'reilly said steve jobs tech
support long term web 2.0 "mr. o'reilly personal brand came back cloud computing meaningful
use
```

Summary

This implementation demonstrates how to efficiently analyze bigrams in text using NLTK by filtering, scoring, and ranking them to extract meaningful pairs. The Jaccard Index offers a quantitative measure of similarity that enhances the understanding of text relationships, making it a valuable technique in natural language processing.

Analyzing Text with Bigrams and Noise Management

1. Proper Names and Phrases Extraction :

- Despite not using special techniques to identify proper names (like those in **Title Case**), many significant names and phrases were successfully extracted from the data.
- Some **noise** remains due to punctuation not being cleaned from tokens, yet the results are still impressive given the minimal effort.

2. Understanding Noise :

- Textual analysis will always contain some noise, even with advanced **natural language processing (NLP)** methods.
- It's important to develop strategies to manage this noise without requiring extensive resources to achieve perfect results.

3. Value of Simple Techniques :

- The analysis demonstrates that even basic techniques can reveal valuable insights from unstructured text data with minimal time investment.
- The findings align with existing knowledge, suggesting that similar methods could be applied to analyze other texts, yielding comparable insights.

4. Discovering New Information :

- While the data might confirm what is already known (e.g., insights about **Tim O'Reilly**), it can also uncover unexpected information, such as mentions of recipes (e.g., "olive oil" and "1/4 cup").

5. Using TF-IDF for Deeper Analysis :

- To explore a specific topic (like “olive oil”), you can use the **TF-IDF** method developed earlier to query the data.
- For example, a search for “olive oil” led to a recipe for cauliflower pancakes, showcasing the practical application of these techniques.

6. Next Steps :

- After identifying interesting topics, you can use **cosine similarity** to find the most similar posts related to your findings (like the cauliflower pancake recipe).

Conclusion

This analysis illustrates the effectiveness of bigrams in revealing significant patterns in text while managing noise. By leveraging techniques like TF-IDF, you can efficiently explore and gain insights from unstructured data.

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Understanding Contingency Tables and Scoring Functions for Bigram Collocations

1. Overview :

- This section explains the technical workings of the **Bigram CollocationFinder** and the **Jaccard scoring function** introduced earlier. If you're less interested in the details, you can skip this part for now.

2. Contingency Tables :

- A **contingency table** is a key data structure used to compute metrics for bigrams. It organizes frequency data for different terms in a bigram.
- **Table Structure** :
 - The table shows frequencies for occurrences of two tokens in a bigram:
 - **token1** : indicates presence of the first token.
 - **~token1** : indicates absence of the first token.
 - The middle four cells reflect the frequencies of the bigram variations, which help calculate similarity metrics.

3. Frequency Counts :

- The contingency table includes frequency counts:
 - **frequency(token1, token2)** : Counts occurrences of both tokens in a bigram.
 - **frequency(~token1, token2)** : Counts occurrences of the second token when the first is absent. This requires scanning all bigrams if no additional data is available.
- To compute these frequencies effectively, having access to a **frequency distribution** of the bigrams or unigrams is beneficial.

4. Calculating Frequencies :

- If only a frequency distribution of bigrams is available:
 - **frequency(token1, token2)** can be directly looked up.
 - To find **frequency(~token1, token2)**, you must scan the bigrams for occurrences of **token2** and subtract **frequency(token1, token2)** from this total.
- If you have a distribution for unigrams (individual tokens), calculations become easier and more efficient.

5. Similarity Metrics :

- The values from the contingency table can be used to compute various **similarity metrics**, which rank bigrams based on their significance. The **Jaccard Index** is one such metric that quantifies similarity by comparing shared and unique elements between sets.

Conclusion

Understanding contingency tables and their role in calculating bigram frequencies is essential for effectively analyzing text data. This knowledge allows for more accurate and efficient computation of similarity metrics, like the Jaccard Index, enhancing the detection of meaningful collocations in text.

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Efficient Calculation of Bigrams Using Contingency Tables

1. Streamlined Bigram Calculation :

- When calculating frequencies in contingency tables, if you have both **unigram** and **bigram** frequency distributions, you can simplify the process using two lookups and an arithmetic operation.
- For example:
 - If the bigram ("mr.", "green") appears **3 times** and the unigram ("green") appears **7 times**, then the bigram (~"mr.", "green") appears **4 times**. This means any token other than "mr." with "green" is counted.

2. Understanding Frequency Expressions :

- The contingency table uses expressions like:
 - **frequency(*, token2)** : Represents the total occurrences of **token2** (noting it in the margin as a shortcut).
 - **frequency(token1, *)** : Helps calculate **frequency(token1, ~token2)**.
 - **frequency(*, *)** : Represents the total number of tokens in the text.

3. Importance of Frequency Counts :

- You need counts for:
 - **frequency(token1, token2)**
 - **frequency(token1, ~token2)**
 - **frequency(~token1, token2)**
- To find **frequency(~token1, ~token2)**, knowing **frequency(,)** is essential.

4. Jaccard Index Explained :

- The **Jaccard Index** measures similarity between two sets. It's calculated as:
$$\text{Jaccard Index} = \frac{\text{Number of items in common}}{\text{Total distinct items in both sets}}$$
- If two sets are identical, the ratio is **1.0**; if completely different, the ratio is **0.0**. Values in between indicate varying degrees of similarity.
- In the context of bigrams, it shows the ratio of the bigram's frequency to the combined frequencies of all bigrams containing any term from the bigram of interest. A higher ratio indicates that the bigram is more likely to convey a meaningful concept.

5. Choosing Scoring Functions :

- Selecting the appropriate scoring function (like the Jaccard Index) depends on:

- Knowledge of the data characteristics.
- Intuition about the analysis.
- Sometimes, a bit of luck.
- For further exploration of association metrics, reference **Foundations of Statistical Natural Language Processing** by Christopher Manning and Hinrich Schuetze.

Conclusion

Understanding how to efficiently calculate bigram frequencies using contingency tables and how to apply scoring functions like the Jaccard Index is crucial for analyzing text data. These methods provide insights into meaningful collocations and enhance text analysis capabilities.

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Key Terms for Building a Collocation Detector

1. Raw Frequency :

- **Definition** : Raw frequency is the ratio of the frequency of a specific n-gram to the total frequency of all n-grams in a text.
- **Purpose** : It helps examine how often a particular collocation appears within the text.

2. Jaccard Index :

- **Definition** : The Jaccard Index is a ratio that measures similarity between two sets. For collocations, it is calculated as the frequency of a specific collocation divided by the total number of collocations containing at least one term from that collocation.
- **Purpose** : It assesses the likelihood that the given terms form a meaningful collocation and ranks potential collocations based on their significance.
- **Mathematical Expression** : Jaccard Index = $\frac{\text{Frequency of collocation}}{\text{Total number of collocations with at least one term}}$

3. Dice's Coefficient :

- **Definition** : Similar to the Jaccard Index, but it gives double weight to agreements between sets.
- **Purpose** : It can be preferred when emphasizing instances where the collocation “token1 token2” appears more frequently.
- **Mathematical Expression** : Dice's Coefficient = $\frac{2 \times \text{Frequency of both terms}}{\text{Total occurrences of each term}}$

4. Likelihood Ratio :

- **Definition** : This metric evaluates the independence between terms that may form a collocation. It is often more suitable than the chi-square test for discovering collocations.
- **Purpose** : It effectively handles data with many infrequent collocations.
- **Calculation** : The likelihood estimates for collocations are computed assuming a **binomial distribution**, based on the occurrences of collocations and their constituent terms.

Summary

These metrics— Raw Frequency , Jaccard Index , Dice's Coefficient , and Likelihood Ratio —are essential for building a collocation detector. They provide different approaches for evaluating the significance and strength of collocations in textual analysis. Understanding and applying these terms will enhance your ability to analyze unstructured text data effectively.

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Key Metrics for Measuring Collocations

1. Chi-square :

- **Definition** : The chi-square test is a statistical method used to assess the independence of two variables. It can determine if two tokens form a collocation based on **Pearson's chi-square test** .
- **Advantage** : Unlike the t-test, chi-square does not require an assumption of normal distribution, making it more widely applicable.

2. Student's t-score :

- **Definition** : The t-score is traditionally used for hypothesis testing, including assessing whether two terms are collocations. It uses a standard distribution for calculations.
- **Advantage** : T-scores consider the frequency of a bigram in relation to its individual components, which helps rank the strength of collocations.
- **Criticism** : The t-test assumes a normal distribution for collocations, which is often not valid.

3. Pointwise Mutual Information (PMI) :

- **Definition** : PMI measures how much knowing one word informs you about another. It quantifies the information gained about a word from its neighboring word.
- **Limitation** : PMI often scores high-frequency words lower than low-frequency words, which is counterintuitive. It is more effective for measuring independence than dependence, making it less suitable for scoring collocations. Sparse data can also hinder PMI's effectiveness.

Tapping into Your Gmail

- **Overview** : Google Buzz provides valuable textual data, but you can also mine your Gmail for insights from numerous messages.
- **Connection to Previous Chapters** : Techniques discussed in Chapter 3, which focus on structured data from email messages, can be applied to both Gmail and Google Buzz for effective text analysis.

Summary

These statistical measures— Chi-square , Student's t-score , and Pointwise Mutual Information (PMI) —are essential for evaluating collocations in text analysis. Understanding their strengths and limitations will help you choose the most

appropriate method for your analysis needs. Additionally, leveraging your Gmail data can enhance your insights alongside Google Buzz.

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Accessing Gmail with OAuth

In early 2010, Google introduced OAuth access for IMAP and SMTP in Gmail, marking a pivotal moment by allowing third-party developers to create applications that access your Gmail data securely without requiring your username and password.

Key Points:

- **OAuth Overview** : This access method enhances security by enabling app integration without sharing login credentials. For detailed mechanics of **Xoauth**, Google's specific OAuth implementation, refer to "No, You Can't Have My Password" on page 85.

Steps to Access Gmail Data:

1. Enable IMAP :

- Go to your **Gmail Account Settings**.
- Select the **"Forwarding and POP/IMAP"** tab and enable **IMAP**.

2. Download Xoauth Tool :

- Visit the **Google Mail Xoauth Tools wiki page**.
- Download the **xoauth.py** command-line utility.
- Follow the instructions to generate an **OAuth token** and **secret** for an "anonymous" consumer.

3. Install Required Libraries :

- Install the **python-oauth2** library using the command: `bash Copy code easy install oauth2`

4. Use Template to Connect :

- Utilize the following template (Example 7-11) to establish an IMAP connection using OAuth:

python Copy code

```
# -*- coding: utf-8 -*- import sys import oauth2 as oauth import oauth2.clients.imap as imaplib # OAUTH_TOKEN and OAUTH_TOKEN_SECRET obtained with xoauth.py OAUTH_TOKEN = sys.argv[1] OAUTH_TOKEN_SECRET = sys.argv[2] GMAIL_ACCOUNT = sys.argv[3] # example@gmail.com url = 'https://mail.google.com/mail/b/%s/imap/' % (GMAIL_ACCOUNT,) # Standard values for Gmail's Xoauth consumer = oauth.Consumer('anonymous', 'anonymous') token = oauth.Token(OAUTH_TOKEN, OAUTH_TOKEN_SECRET) conn = imaplib.IMAP4_SSL('imap.googlemail.com') conn.debug = 4 # Set to the desired debug level conn.authenticate(url, consumer, token) conn.select('INBOX')
```

Notes:

- Using the **anonymous consumer credentials** from **xoauth.py** is sufficient for personal data access. You can later register for a “**trusted**” **client application** when necessary.

Summary

This guide provides the essential steps to set up OAuth access for Gmail, allowing for secure data access without compromising your credentials. By enabling IMAP and using the provided template, you can start interacting with your Gmail account programmatically.

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Accessing Your INBOX Data

Step 1: Fetch and Parse Message Data

Once you have access to your mail data, the next step is to fetch and parse email messages.

Fetching and Parsing Email Messages

- **IMAP Protocol** : The IMAP (Internet Message Access Protocol) can be complex, but you don't need extensive knowledge to search and retrieve emails.
- **Searching for Messages** :
 - Use `imaplib` for basic operations. Many online examples illustrate how to perform searches.
 - To search for messages from yourself, use:

```
python Copy code conn.search( None , ' (FROM "me") ' )
```


Here, `None` is an optional character set, and `' (FROM "me") '` looks for messages sent by the authenticated user.
 - To find messages with a specific subject, use:

```
python Copy code ' (SUBJECT "foo") '
```
- **IMAP Queries** : Explore more options in **RFC 3501** , which outlines the IMAP specification.
- **Search Response** :
 - The response from `imaplib` is a tuple, e.g.,:

```
python Copy code ( 'OK' , [ '506 527 566' ] )
```
 - This indicates the status and contains a list of space-separated message IDs.
- **Parsing Email Content** :

- To convert these IDs into **RFC 822-compliant** messages, additional parsing is required.
- Reuse code from Example 3-3, which utilizes the **email module** to parse messages into a usable format.

Example: Extracting Email Bodies

Script Overview : The following Python script demonstrates a simple workflow for extracting email bodies from Gmail messages returned from a search.

python Copy code

```
# -*- coding: utf-8 -*-
import oauth2 as oauth
import oauth2.clients.imap as imaplib
import os
import sys
import email
import quopri
import json
from BeautifulSoup import BeautifulSoup
# OAuth tokens and Gmail account details
OAUTH_TOKEN = sys.argv[1] # Obtained with xoauth.py
OAUTH_TOKEN_SECRET = sys.argv[2] # Obtained with xoauth.py
GMAIL_ACCOUNT = sys.argv[3] # e.g., example@gmail.com
Q = sys.argv[4] # Search query
```

Key Points

- **Accessing Mail** : Understand the basics of fetching and parsing messages.
- **IMAP Protocol** : Utilize `imaplib` for searching emails.
- **Response Handling** : Be prepared to parse the response for message IDs.
- **Reusing Code** : Adapt existing code to handle email content effectively.

This approach simplifies the process of accessing and managing your email data efficiently.

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Gmail IMAP Access and Message Handling

Step 1: Set Up the URL and Authentication

- **URL Configuration :**

python Copy code `url = 'https://mail.google.com/mail/b/%s/imap/' % (GMAIL_ACCOUNT,)`

- **OAuth Authentication :**

- Use standard values for Gmail's **xoauth** implementation: python Copy code `consumer = oauth.Consumer('anonymous', 'anonymous')`
`token = oauth.Token(OAUTH_TOKEN, OAUTH_TOKEN_SECRET)`

- **Connect to IMAP :**

python Copy code `conn = imaplib.IMAP4_SSL('imap.googlemail.com')`
`conn.debug = 4 # Set debug level for troubleshooting`
`conn.authenticate(url, consumer, token)`

- **Select Inbox :**

```
python Copy code conn.select( 'INBOX' )
```

Step 2: Clean and Process Email Content

- **Function: cleanContent(msg) :**

- **Purpose :** Decode and clean email messages.
- **Process :**
 - Decode from **quoted-printable** format.
 - Remove **HTML tags** using BeautifulSoup:

```
python Copy code soup = BeautifulSoup(msg) return ''.join(soup.findAll(text= True ))
```

- **Function: jsonifyMessage(msg) :**

- **Purpose :** Convert message into JSON format.
- **Process :**
 - Initialize a JSON structure:

```
python Copy code json_msg = { 'parts' : [] }
```
 - Decode message fields (To, CC, BCC) into UTF-8, ignoring errors.
 - Handle potential multiple items in To, CC, and BCC:

```
python Copy code for k in [ 'To' , 'Cc' , 'Bcc' ]: if not json_msg.get(k): continue json_msg[k] = json_msg[k].replace( '\n' , ' ' ).replace( '\t' , ' ' ).replace( '\r' , ' ' ).replace( ' ' , ' ').split( ',' )
```
 - Iterate through message parts:

```
python Copy code for part in msg.walk(): if part.get_content_maintype() == 'multipart' : continue json_part = { 'contentType' : part.get_content_type(), 'content' : cleanContent(part.get_payload(decode= False ).decode('utf-8' , 'ignore' )) } json_msg[ 'parts' ].append(json_part )
```

Key Points

- **Setup :** Authenticate to Gmail's IMAP using OAuth.
- **Email Selection :** Focus on the **INBOX** folder.
- **Content Processing :** Use functions to decode and clean email content for JSON representation.
- **JSON Structure :** Organize email data into a structured format for easier access and manipulation.

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Handling Email Messages and Data Extraction

Error Handling :

python Copy code

```
except Exception as e: sys.stderr.write( 'Skipping message - error encountered (%s)' % ( str( e), )) finally : return json_msg
```

- This block captures any errors encountered during message processing and logs them, ensuring that the function

still returns a JSON message.

Step 1: User Query and Message Search

- **Consume User Query :**

- Search for messages based on the subject: python Copy code

```
(status, data) = conn.search( None , '(SUBJECT "%s")' % (Q, ))
```

- **Extract Message IDs :**

python Copy code

```
ids = data[ 0 ].split()
```

- **Fetch Messages :**

- Initialize an empty list for messages: python Copy code

```
messages = []
```
- Loop through each ID to fetch the message: python Copy code

```
for i in ids: try : (status, data) = conn.fetch(i, '(RFC822)' ) messages.append(email.message_from_string (data[ 0 ][ 1 ])) except Exception as e: 'Print error fetching message %s. Skipping it.' % (i, )
```

Step 2: Convert Messages to JSON Format

- **JSONify Messages :**

python Copy code

```
jsonified_messages = [jsonifyMessage(m) for m in messages]
```

- **Extract Content :**

- Separate the text content from each message for analysis: python Copy code

```
content = [p[ 'content' ] for m in jsonified_messages for p in m[ 'parts' ]]
```
- Note: Content may still have formatting issues (line breaks, etc.).

Step 3: Save JSON Data to File

- **Directory Check :**

- Create an output directory if it doesn't exist: python Copy code

```
if not os.path.isdir( 'out' ): os.mkdir( 'out' )
```

- **File Naming and Writing :**

python Copy code

```
filename = os.path.join( 'out' , GMAIL_ACCOUNT .split( "@" )[ 0 ] + '.gmail.json' ) with open (filename, 'w' ) as f: f.write(json.dumps(jsonified_messages )) print >> sys.stderr, "Data written out to" , f.name
```

Additional Considerations

- **Text Cleansing :** After parsing, further text cleansing is necessary for display or advanced **NLP** (Natural Language Processing) tasks. The content can be refined for **collocation analysis** .
- **Visualization Opportunity :** Consider creating a graph to visualize linkages between messages based on shared **bigrams** using a custom metric.

Conclusion

- This guide covers how to extract and process email data from Gmail, handle errors, convert messages to JSON, and save the output for further analysis. While it introduces essential concepts, it also highlights the complexity of building a search engine and extracting meaningful insights from unstructured text.

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Understanding Information Retrieval Limitations

Overview :

- **Information Retrieval** is a multibillion-dollar industry, crucial for the functionality of search engines like Google and Yahoo!. This section highlights limitations in **TF-IDF** , **cosine similarity** , and other related concepts.

TF-IDF Limitations :

- **Bag of Words Model :**
 - **Definition :** TF-IDF treats documents as collections of words without considering order.
 - **Example :** The queries "Green Mr." and "Mr. Green" yield the same results, which overlooks the importance of word order.
- **N-gram Analysis :**
 - While n-gram analysis can help account for term order and collocations, TF-IDF still assumes that all identical tokens have the same meaning.
- **Homonyms :**
 - Example: Words like "bank" (financial institution vs. riverbank) illustrate that identical terms can have different meanings based on context.
- **Semantic Search :**
 - Unlike traditional TF-IDF, semantic search engines contextualize search terms, allowing differentiation based on intended meaning (e.g., person, location, organization).

Cosine Similarity Limitations :

- **Similar Issues to TF-IDF :**
 - Like TF-IDF, cosine similarity does not consider context or term order.
 - Assumes that proximity in vector space implies similarity, which is not always valid, particularly for homonyms.

- **Dependence on TF-IDF :**

- Our implementation of cosine similarity relies on TF-IDF scoring, meaning any TF-IDF inaccuracies directly affect cosine similarity results.

Challenges in Analyzing Unstructured Text :

- **Details Matter :**

- Accurate analysis requires careful management of seemingly minor details, such as string comparisons.

- **Case Sensitivity :**

- Normalizing text to lowercase can lead to loss of important distinctions. For example, "Mr. Green" and "Web 2.0" might lose meaningful context if normalized improperly.

Conclusion

- Understanding the limitations of TF-IDF and cosine similarity is crucial for improving information retrieval systems. Acknowledging the importance of context and word order, as well as the nuances of language, can guide the development of more advanced and effective search technologies.

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Key Considerations in Information Retrieval

Understanding Context :

- Recognizing the context of words, such as "Green," is crucial. Advanced **Natural Language Processing (NLP)** techniques can retain this context, which is lost in the **bag-of-words** approach.

Tokenization Issues :

- Our implementation uses a **split** method to tokenize text, which may leave trailing punctuation.
 - **Example :** The token "study." is different from "study" (without the period), affecting frequency calculations in **TF** (Term Frequency) and **IDF** (Inverse Document Frequency).

Stemming Words :

- **Stemming** can be beneficial to treat variations of the same word as a single term. This simplifies analysis by reducing the number of unique tokens.
 - Explore the **nlk.stem** package for effective stemming methods.

Engineering Considerations for Production :

- **Indexes and Caching** : Essential for improving query times in large datasets.
- **Batch Processing** : Analyzing massive amounts of text requires robust systems like **Hadoop** , which can be costly, particularly in cloud environments like Amazon's **Elastic Compute Cloud** .

Closing Remarks

- This chapter covers fundamental concepts in **Information Retrieval (IR)** , including **TF-IDF** , **cosine similarity** , and **collocations** .
- Understanding these foundational techniques provides insight into the limitations of traditional search methods and highlights the advancements in **entity-centric** techniques discussed in Chapter 8.
- For practical applications, consider using **Scrapy** , a user-friendly web scraping framework, or explore **Dumbo** for writing Hadoop programs in Python if you're interested in large-scale data processing.

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Chapter 8: Natural Language Processing (NLP) and Blogs

Overview :

- This chapter introduces **Natural Language Processing (NLP)** and its application to unstructured data found in blogs. It aims to provide a foundational understanding of NLP while allowing practical application.

Chapter Goals :

- **Basic Understanding** : Provide essential knowledge of NLP to enable you to mine data effectively.
- **Technical Insights** : Offer enough detail for immediate implementation of NLP techniques, such as:
 - Automatically generating abstracts.
 - Extracting important entities.

Approach :

- The chapter adopts a **Pareto Principle** approach, focusing on the crucial 20% of skills that will enable 80% of the work.
- Acknowledges the complexity of NLP, emphasizing that comprehensive coverage would require extensive study beyond this chapter.

Prerequisites :

- Although not mandatory, familiarity with **Chapter 7** is recommended for a better understanding of:
 - **TF-IDF** (Term Frequency-Inverse Document Frequency).
 - **Vector Space Models** .
- Understanding these concepts is essential, as they are closely linked to the foundations of NLP.

Data Source :

- The primary data source for this chapter is **blogs** . They are chosen because:
 - They are a significant part of the social web.
 - They are well-suited for text mining.
 - The distinction between blog posts and articles is increasingly blurred.

NLP Complexity :

- The chapter begins with a discussion on the challenges of NLP, illustrating how it differs from traditional text analysis methods.
- Emphasizes the inherent difficulties in processing natural language, highlighting the need for nuanced approaches.

Conclusion

- This chapter serves as a practical introduction to NLP, specifically applied to blogs, equipping you with the necessary tools to start working with unstructured text data effectively.

Syntax and Semantics in Natural Language Processing (NLP)

Introduction :

- This section contrasts the techniques from earlier chapters with the complexities of **Natural Language Processing (NLP)** . It emphasizes the limitations of methods like **TF-IDF** and **cosine similarity** , which do not capture deep semantic meaning.

Limitations of TF-IDF and Cosine Similarity :

- These models rely on **syntax** (basic structure) rather than **semantics** (meaning), using whitespace to separate tokens.
- They can identify important tokens based on frequency and statistical similarity but fail to provide context for what each token means.

Complexities of NLP :

- **Heteronyms and Homographs** : Words like "fish" or "bear" can function as nouns or verbs, complicating interpretation.
- Achieving a full understanding of NLP is challenging and equated to passing the **Turing Test** , which demonstrates human-like intelligence in machines.

Human vs. Machine Interpretation :

- **Structured Data** : Easier to analyze as it has predefined meanings for each field.
- **Natural Language Data** : Requires nuanced understanding for even simple tasks. For example:
 - Counting sentences might be easy for humans due to basic grammar knowledge, but machines need complex algorithms.

Sentence Detection :

- Machines can detect sentence boundaries quickly and accurately in well-formed data.
- However, knowing how words are used in sentences requires additional context.

Example :

- The phrase "That's the bomb" can be parsed easily, but its meaning is ambiguous without context:
 - It could mean something excellent or refer to a weapon.

Conclusion

- Understanding both **syntax** and **semantics** is crucial in NLP. While machines can analyze structure, interpreting meaning often requires context beyond the immediate text. This highlights the complexity and depth of natural language, emphasizing the challenges faced in NLP applications.

Understanding Natural Language Processing (NLP)

Core Concept :

- NLP involves transforming a **syntactically correct** document, filled with symbols, into meaningful **semantics** . This includes understanding references, such as what the pronoun “that” refers to in context.

Sentence Detection: A Thought Exercise

Task Overview :

- Detecting sentences is a foundational step in NLP. It's essential to recognize the complexities and limitations of simple approaches.

Common Approach :

- A naive method for sentence detection is to count punctuation marks like periods, question marks, and exclamation points. However, this method can lead to significant errors.

Example :

- Consider the text:
“Mr. Green killed Colonel Mustard in the study with the candlestick. Mr. Green is not a very nice fellow.”
- If we split on periods without context, we get:
`css Copy code ['Mr' , 'Green killed Colonel Mustard in the study with the candlestick' , 'Mr' , 'Green is not a very nice fellow' , '']`
- This result shows that simply using periods as delimiters is insufficient due to abbreviations like "Mr." which can mislead the algorithm.

Complexity of NLP Tasks

Limitations of Simple Heuristics :

- Relying on basic rules can produce high error margins. The example demonstrates that understanding context is vital for accurate sentence detection.

Collocation and Tokenization :

- In more extensive text, **collocations** (like “Mr. Green”) may complicate tokenization. Recognizing these as single units requires advanced analysis.

Identifying Key Topics

- Recognizing key topics (e.g., “Mr. Green”, “Colonel Mustard”, “the study”, “the candlestick”) is not straightforward. While humans can easily identify these, teaching a machine to do so is a complex challenge.

Conclusion

- NLP is a nuanced field that requires careful consideration of context, semantics, and the limitations of simple rule-based approaches. Understanding these complexities is crucial for developing effective NLP solutions.

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Key Considerations for NLP

Challenges in NLP :

- When developing an NLP algorithm, consider using methods like **Title Case detection** with **regular expressions** , and maintain a list of common abbreviations to identify **proper noun phrases** .
- However, think about the **margin of error** when dealing with arbitrary English text or other languages like **Spanish** , **French** , or **Italian** . Simple solutions may not work well across different contexts, such as poorly formed text messages or tweets.

Importance of Text Analytics :

- The complexity of text analytics arises from the vast amounts of textual data available today. While this can be daunting, it's also an exciting challenge in a rapidly evolving field.

Encouragement :

- Although the task may seem overwhelming, tools like **NLTK** (Natural Language Toolkit) can effectively handle many NLP scenarios with minimal setup.

Typical NLP Pipeline with NLTK

The NLP process typically follows these steps:

1. **End of Sentence (EOS) Detection**
2. **Tokenization**
3. **Part-of-Speech Tagging**
4. **Chunking**
5. **Extraction**

Sample Text for Illustration :

- "Mr. Green killed Colonel Mustard in the study with the candlestick. Mr. Green is not a very nice fellow."

Detailed Steps in the Pipeline

1. EOS Detection :

- This step identifies and separates sentences in a text, allowing for logical units of thought to be analyzed. Sentences have predictable syntax, making them easier to process.
- NLTK can parse sentences effectively, which sets the stage for the next step: **Tokenization** .

2. Tokenization :

- After detecting sentence boundaries, tokenization breaks down sentences into smaller components, typically words or phrases, facilitating further analysis.

By following these steps in the NLP pipeline, you can begin to understand and manipulate textual data more effectively, leveraging tools like NLTK to assist in the process.

Working with NLTK for NLP Tasks

1. Importing NLTK :

- Start by importing the NLTK library, which is essential for various NLP tasks.

python Copy code

```
import nltk
```

2. Sentence Tokenization :

- Use `nltk.tokenize.sent_tokenize` to split text into sentences.

Example :

python Copy code

```
txt = "Mr. Green killed Colonel Mustard in the study with the candlestick. Mr. Green is not a very nice fellow."  
sentences = nltk.tokenize.sent_tokenize(txt)
```

- **Output :**

python Copy code

```
['Mr. Green killed Colonel Mustard in the study with the candlestick.', 'Mr. Green is not a very nice fellow']
```

- This method improves upon simple punctuation-based splitting by accurately identifying sentence boundaries.

3. Tokenization :

- After sentences are identified, use `nltk.tokenize.word_tokenize` to break each sentence into words (tokens).

Example :

python Copy code

```
tokens = [nltk.tokenize.word_tokenize(s) for s in sentences]
```

- **Output :**

python Copy code

```
[[ 'Mr.', 'Green', 'killed', 'Colonel', 'Mustard', 'in', 'the', 'study', 'with', 'the', 'candlestick', '.' ], [ 'Mr.', 'Green', 'is', 'not', 'a', 'very', 'nice', 'fellow', '.' ]]
```

- This method correctly identifies end-of-sentence markers and manages punctuation better than basic whitespace splitting.

4. Part-of-Speech (POS) Tagging :

- Assign part-of-speech tags to each token using `nltk.pos_tag` .

Example :

python Copy code

```
pos_tagged_tokens = [nltk.pos_tag (t) for t in tokens]
```

- **Output :**

python Copy code

```
[[ ('Mr.', 'NNP'), ('Green', 'NNP'), ('killed', 'VBD'), ('Colonel', 'NNP'), ('Mustard', 'NNP'), ('in', 'IN'), ('the', 'DT'), ('study', 'NN'), ('with', 'IN'), ('the', 'DT'), ('candlestick', 'NN'), (',', ',' )], [ ('Mr.', 'NNP'), ('Green', 'NNP'), ('is', 'VBZ'), ('not', 'RB'), ('a', 'DT'), ('very', 'RB'), ('nice', 'JJ'), ('fellow', 'JJ'), (',', ',' )]]
```

- **Tags Explained :**

- **NNP** : Proper Noun
- **VBD** : Verb, Past Tense
- **JJ** : Adjective
- **DT** : Determiner
- **IN** : Preposition
- **RB** : Adverb
- Understanding these tags enables more powerful analysis, such as identifying and chunking **noun phrases** for further exploration.

Summary

The steps outlined above demonstrate a basic yet effective NLP pipeline using NLTK. From sentence detection to tokenization and POS tagging , each stage enhances the analysis of text, making it easier to extract meaningful insights.

Understanding NLP: Chunking and Extraction

1. Chunking :

- **Definition** : This process analyzes tagged tokens in a sentence to combine them into **compound tokens** that represent logical concepts.
- **Method** : NLTK's `chunk.RegexpParser` allows for custom grammar definitions, but this topic is beyond the chapter's scope. For more details, refer to Chapter 9 of *Natural Language Processing with Python* .
- **Purpose** : Chunking helps to identify entities within the text, setting the stage for named entity recognition.

2. Extraction :

- **Definition** : This step analyzes each chunk and labels them as **named entities** , which can include:
 - **People**
 - **Organizations**
 - **Locations**

Example of Extraction :

python Copy code

```
ne_chunks = nltk.batch_ne_chunk (pos_tagged_tokens )
```

- **Output** :

python Copy code

```
[Tree( 'S' , [Tree( 'PERSON' , [( 'Mr.' , 'NNP' )]), Tree( 'PERSON' , [( 'Green' , 'NNP' )]), ( 'killed' , 'VBD' ), Tree( 'ORGANIZATION' , [( 'Colonel' , 'NNP' ), ( 'Mustard' , 'NNP' )]), ...])]
```

- The output shows a structured tree where tokens are categorized:
 - “Mr. Green” is identified as a **person** .
 - “Colonel Mustard” is mistakenly categorized as an **organization** .

Visualizing Results :

- You can visualize these chunks with the `draw()` method, which creates a graphical representation of the structure.

Summary

- **Chunking** and **extraction** are vital components of the NLP process that help in understanding the entities within text. While NLTK provides tools for these tasks, creating a **state-of-the-art NLP solution** requires significant

investment and expertise. For serious applications, consider using established commercial solutions alongside open-source options for best results.

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NLP and Specialized Consulting

1. Active Research Field :

- **NLP (Natural Language Processing)** is a rapidly evolving area, and **cutting-edge techniques** often require specialized consulting.
- Advanced solutions are not yet standardized or commoditized, making expert guidance valuable.

2. Visualization with NLTK :

- NLTK can integrate with drawing toolkits, enabling you to visualize **chunked outputs** more intuitively than just viewing raw text.

3. Using NLTK "As-Is" :

- This chapter assumes you'll use NLTK in its existing form.
- If you have extensive knowledge (like a PhD in computational linguistics), you could modify NLTK for specialized needs.

Sentence Detection in Blogs with NLTK

1. Importance of Sentence Detection :

- **Sentence detection** is a foundational task in building an NLP pipeline.
- It has significant applications, including **document summarization** .

2. Fetching Blog Data :

- To start, you'll need high-quality blog data.
- The **feedparser module** is recommended for this task.

Example Code :

- The following code snippet demonstrates how to fetch blog posts and save them as JSON:

python Copy code

```
# -*- coding: utf-8 -*- import os import sys from datetime import datetime as dt import json import feedparser from BeautifulSoup import BeautifulSoup from nltk import clean_html # Example feed: # http://feeds.feedburner.com/oreilly/radar/atom FEED_URL = sys.argv[ 1 ]
```

- You can choose to store the posts in any format or location that suits your needs.

Summary

- NLP is complex and continuously developing, often requiring expert input.
- Visual tools enhance understanding of NLP processes.
- Start your NLP journey with sentence detection, using feedparser to gather relevant blog data.

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Code Explanation for Parsing Blog Data

1. Function to Clean HTML :

- The `cleanHtml` function uses `BeautifulStoneSoup` to remove HTML tags and convert entities:

python Copy code

```
def cleanHtml ( html ): return BeautifulSoup(clean_html (html), convertEntities=BeautifulStoneSoup.HTML_ENTITIES ).contents[ 0 ]
```

2. Fetching Blog Data :

- The `feedparser` module is used to parse the feed URL provided:

python Copy code

```
fp = feedparser.parse(FEED_URL ) print "Fetched %s entries from %s" % ( len (fp.entries), fp.feed.title)
```

- This line outputs the number of entries fetched and the title of the feed.

3. Storing Blog Posts :

- Blog posts are collected in a list, `blog_posts`, with each entry containing the **title**, **cleaned content**, and **link** :

python Copy code

```
blog_posts = [] for e in fp.entries: blog_posts.append({'title': e.title, 'content': cleanHtml(e.content[0].value), 'link': e.links[0].href})
```

4. Saving Output :

- If the output directory (`out`) does not exist, it is created:

python Copy code

```
if not os.path.isdir('out'): os.mkdir('out')
```

- The blog posts are saved as a JSON file named after the feed title and the current date:

python Copy code

```
out_file = '%s_%s.json' % (fp.feed.title, dt.utcnow()) f = open(os.path.join(os.getcwd(), 'out', out_file), 'w') f.write(json.dumps(blog_posts)) f.close() print >> sys.stderr, 'Wrote output file to %s' % (f.name,)
```

NLP Analysis with NLTK

1. Assumption of Good Grammar :

- Using reputable sources allows the assumption of **good English grammar**, which helps NLTK's sentence detection tools work effectively.

2. Using NLTK for Sentence and Word Tokenization :

- The following code demonstrates the use of NLTK's sentence and word tokenization:

python Copy code

```
import sys import json import nltk # Load output from the previous script BLOG_DATA = sys.argv[1] blog_data = json.loads(open(BLOG_DATA).read())
```

- A custom list of **stopwords** is created, adding common punctuation and contractions:

python Copy code

```
stop_words = nltk.corpus.stopwords.words('english') + [':', ',', '-', '\s', ]
```

Summary

- The provided code efficiently fetches and cleans blog data, storing it in a structured JSON format.
- NLTK tools for **sentence** and **word tokenization** are set up to analyze the cleaned text, leveraging assumptions of good grammar for effective processing.

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Analyzing Blog Data with NLTK

1. Stopwords List :

- A list of **stopwords** is created to filter out common words that don't add much meaning. This list includes various punctuation and contractions:

python Copy code

```
stop_words = nltk.corpus.stopwords.words('english') + ['?', ')', '(', ':', '\n', '\re', '"', '\t', '}', '{']
```

2. Processing Each Blog Post :

- For each post in the `blog_data`, the following steps are performed:

3. Sentence Tokenization :

- **Sentences** are extracted from the post's content using `nltk.tokenize.sent_tokenize` :

python Copy code

```
sentences = nltk.tokenize.sent_tokenize(post['content'])
```

4. Word Tokenization and Normalization :

- **Words** are tokenized from each sentence and converted to lowercase:

python Copy code

```
words = [w.lower() for sentence in sentences for w in nltk.tokenize.word_tokenize(sentence)]
```

5. Frequency Distribution :

- A **frequency distribution** of words is created to analyze how often each word appears:

python Copy code

```
fdist = nltk.FreqDist(words)
```

6. Basic Statistics :

- Various statistics are calculated:

- **Total Words** : Total number of words in the post.

```
python Copy code num_words = sum([i[1] for i in fdist.items()])
```

- **Unique Words** : Count of unique words in the post.

```
python Copy code num_unique_words = len(fdist.keys())
```

- **Hapaxes** : Words that appear only once in the post.

```
python Copy code num_hapaxes = len(fdist.hapaxes())
```

7. Top Frequent Words :

- The top 10 most frequent words, excluding stopwords, are identified:

python Copy code

```
top_10_words_sans_stop_words = [w for w in fdist.items() if w[0] not in stop_words][:10]
```

8. Output Results :

- The results are printed for each post, including:
 - **Title** of the post.
 - **Number of Sentences** .
 - **Total Number of Words** .
 - **Number of Unique Words** .
 - **Number of Hapaxes** .
 - **Top 10 Most Frequent Words** without stopwords:

python Copy code

```
print post['title'] print '\tNum Sentences:' .ljust(25), len(sentences) print '\tNum Words:' .ljust(25), num_words print '\tNum Unique Words:' .ljust(25), num_unique_words print '\tNum Hapaxes:' .ljust(25), num_hapaxes print '\tTop 10 Most Frequent Words (sans stop words):' .ljust(25), '\n\t\t' .join(['%s (%s)' % (w[0], w[1]) for w in top_10_words_sans_stop_words])
```

Summary

- This code effectively processes blog data by tokenizing sentences and words, analyzing word frequency, and presenting key statistics. It emphasizes important metrics like **total words** , **unique words** , and the **most frequent terms** , aiding in the understanding of the blog's content.

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Understanding NLTK Tokenization

1. Tokenization Functions :

- **sent tokenize** and **word tokenize** are key functions in NLTK for breaking text into sentences and words, respectively.
- NLTK recommends using the **PunktSentenceTokenizer** for sentences and the **TreebankWordTokenizer** for words.

2. PunktSentenceTokenizer :

- This tokenizer detects **abbreviations** and uses **collocation patterns** to parse sentences intelligently.
- It employs **regular expressions** to recognize common punctuation usage.
- The underlying algorithm is an **unsupervised learning** model, meaning it learns from the text itself without needing explicit annotations.
- It analyzes features like **capitalization** and **co-occurrences** of tokens to determine sentence boundaries.
- For more detailed insights, refer to the paper "Unsupervised Multilingual Sentence Boundary Detection" by Tibor Kiss and Jan Strunk.

3. TreebankWordTokenizer :

- This tokenizer is recommended over simpler options like the **WhitespaceTokenizer** , which splits text only by spaces.
- The TreebankWordTokenizer follows conventions from the **Penn Treebank Project** and provides nuanced tokenization.
- Notably, it separates components in **contractions** (e.g., "I'm" becomes "I" and "m") and handles possessive forms of nouns distinctly.
- This detailed parsing helps in advanced grammatical analysis, making it easier to examine relationships between subjects and verbs.

4. Treebank Concept :

- A **treebank** is a corpus that contains sentences tagged with detailed linguistic information, allowing for structured grammatical analysis. The term emphasizes its role as a collection (or "bank") of syntactically parsed sentences.

Summary

NLTK's tokenization tools, specifically the `PunktSentenceTokenizer` and `TreebankWordTokenizer`, are essential for effective text processing. They provide a sophisticated approach to understanding sentence and word structures, which is vital for deeper linguistic analysis and natural language processing tasks.

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Simplified Notes on Tokenization and NLP Pipeline

1. Using Tokenizers :

- If advanced tokenizers like **TreebankWordTokenizer** or **PunktWordTokenizer** are challenging, you can use the **WhitespaceTokenizer** as a simpler alternative.
- Simpler tokenizers can be beneficial, especially when handling data with inline **URLs**, which advanced tokenizers may misinterpret and break into multiple tokens.

2. Sentence and Word Tokenization Process :

- The process involves first parsing text into **sentences** and then into **tokens** (words).
- However, errors in sentence detection can propagate, affecting the accuracy of subsequent processing. For example, mistaking "Mr." for a sentence boundary can lead to difficulties in recognizing entities like "Mr. Green".

3. Importance of Error Handling :

- The sophistication of the **NLP stack** affects how well it handles these errors. Advanced models can potentially incorporate specialized logic to correct such mistakes.
- The **PunktSentenceTokenizer** is trained on the **Penn Treebank corpus** and generally performs well, making it a reliable choice for sentence detection.

4. Frequency Distribution (FreqDist) :

- The end goal of tokenization is to create a **FreqDist** object, which counts the frequency of each token.

5. Building an NLP Pipeline :

- This section introduces the initial step of creating an **NLP pipeline** . While we haven't yet covered **part-of-speech tagging** or **chunking** , this foundational understanding is crucial.
- Even though simply splitting text on whitespace can yield useful information, investing time in understanding tokenization enhances overall data analysis.

6. Next Steps :

- The next section will apply what you've learned by exploring a **document summarization algorithm** that uses sentence segmentation and frequency analysis.

Summary

Understanding and selecting the right tokenizer is essential for building an effective NLP pipeline. While advanced tools offer detailed parsing, simpler methods can be effective in specific contexts, particularly when dealing with complex data formats. Recognizing the potential for error propagation emphasizes the need for robust error handling in NLP tasks.

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Notes on Document Summarization

1. Importance of Sentence Detection :

- Effective **sentence detection** is crucial in **Natural Language Processing (NLP)** as it allows for **text mining** capabilities, including **document summarization** .

2. Document Summarization Overview :

- One of the simplest methods for document summarization traces back to a 1958 paper by **H.P. Luhn** titled "The Automatic Creation of Literature Abstracts."
- Luhn's technique focuses on filtering out sentences containing frequently occurring **keywords** that are close to one another in the text.

3. Historical Context :

- Luhn's original work involved extensive manual programming on **mainframe computers** , which contrasts sharply with the simplicity of modern implementations, such as in Python.

4. Basic Implementation :

- Example 8-3 showcases a basic implementation of Luhn's summarization algorithm, which is structured as follows:

Example Code Structure:

- **Parameters :**

- `N = 100` : Number of words to consider.
- `CLUSTER_THRESHOLD = 5` : Distance between words to consider significant.
- `TOP_SENTENCES = 5` : Number of sentences to return in the summary.

- **Functionality :**

- The function `score_sentences` scores each sentence based on its importance by checking the presence of **important words**.

5. Scoring Sentences :

- The scoring process involves:
 - Tokenizing sentences.
 - For each sentence, checking the presence of important words and calculating their indices.

Summary

Understanding the basics of document summarization, as demonstrated by Luhn's method, highlights the significance of keyword identification and sentence structure in extracting essential information from texts. This foundational knowledge is pivotal for developing more advanced NLP applications.

Notes on Document Summarization Algorithm

1. Sentence Scoring Process :

- The scoring function `score_sentences` analyzes sentences based on the presence of **important words**.
- It maintains a list called `word_idx` to store indices of important words found in each sentence.

2. Handling Missing Words :

- If an important word is not found in a sentence, a **ValueError** is raised, which is caught to avoid interruption.

3. Clustering Important Words :

- After gathering indices, the algorithm checks for clusters of important words based on a **maximum distance threshold** defined by `CLUSTER_THRESHOLD`.
- A new cluster starts when the gap between consecutive important words exceeds this threshold.

4. Scoring Clusters :

- Each cluster is scored using the formula:
 - **Score** = $\frac{\text{(significant words in cluster)}^2}{\text{total words in cluster}}$
- The highest score from the clusters within a sentence becomes the score for that sentence.

5. Summarization Function :

- The `summarize` function handles the overall process:
 - **Tokenization** : Sentences are tokenized using `nltk.tokenize.sent_tokenize`.
 - **Normalization** : Sentences are converted to lowercase.
 - **Word Collection** : Words from all sentences are gathered and converted to lowercase.

6. Frequency Distribution :

- The frequency of each word is calculated using `nltk.FreqDist`, which helps identify the most common words.

7. Top Words Selection :

- The algorithm identifies the top **N** important words that are not stopwords.

Summary

This document summarization algorithm emphasizes the importance of identifying and clustering significant words within sentences. By scoring these clusters, it effectively selects the most relevant sentences for summarization. Understanding this process is crucial for building effective text mining and summarization tools in NLP.

Document Summarization Approaches

1. Summarization Approach 1: Mean and Standard Deviation Filtering

- **Objective** : Filter out less significant sentences based on their scores.
- **Method** :
 - Calculate the **average score** of all sentences using `numpy.mean` .
 - Calculate the **standard deviation** of the scores with `numpy.std` .
 - Identify significant sentences where the score exceeds:
 - **Average + 0.5 × Standard Deviation** .
- **Result** : Creates a list of sentences (`mean_scored`) that meet the significance criteria.

2. Summarization Approach 2: Top N Ranked Sentences

- **Objective** : Retrieve the highest-ranked sentences.
- **Method** :
 - Sort all scored sentences by their score.
 - Select the **top N sentences** based on scores, specified by `TOP_SENTENCES` .
 - Re-sort these top sentences by their original index for logical order.
- **Result** : Forms a list of the top-ranked sentences (`top_n_scored`).

3. Returning Summaries

- The function returns a dictionary containing:
 - **top_n_summary** : List of top N sentences.
 - **mean_scored_summary** : List of significant sentences based on the mean and standard deviation filtering.

Example Execution

- **Input** : Blog data from a specified JSON file, such as Tim O'Reilly's post "The Louvre of the Industrial Age".
- **Output** : For each blog post, it prints:
 - The title of the post.
 - The **Top N Summary** : Sentences deemed most significant.
 - The **Mean Scored Summary** : Sentences that pass the filtering threshold.

Summary

These two summarization approaches allow for effective extraction of key sentences from a document. The first approach focuses on statistical filtering based on sentence scores, while the second emphasizes simply selecting the

Summary of Tim O'Reilly's Visit to The Henry Ford Museum

Overview : Tim O'Reilly describes his experience at The Henry Ford Museum in Dearborn, Michigan, highlighting its significance as a tribute to the Industrial Age, akin to the Louvre for industrial innovations.

Key Highlights :

- **Favorite Artifact** : The museum features a block of concrete that includes **Luther Burbank's shovel** and **Thomas Edison's** signature and footprints, representing the connection between agriculture and industrial innovation.
- **Museum's Purpose** : Opened in **1929** , it showcases the transformation of the world through innovation, particularly that of **Henry Ford** , who aimed to honor this evolution.
- **Remarkable Exhibits** : The museum houses incredible machines, including:
 - **Steam engines** and **coal-fired electric generators** .
 - The first **precision lathes** , described as the "makerbot of the 19th century".
 - A **ribbon glass machine** that produced nearly all incandescent lightbulbs in the 1970s.
 - Various historical artifacts related to transportation, such as **combine harvesters** , **railroad locomotives** , **cars** , and even an **early McDonald's** .

Aesthetic and Engineering Evolution : O'Reilly notes the transformation of machines from functional tools to beautiful works of engineering, emphasizing the advancements in materials, workmanship, and design over a century.

Personal Reflection : He expresses a newfound appreciation for Detroit and The Henry Ford, comparing its worthiness to visit to renowned art museums worldwide, such as the Vatican Museum and the Uffizi Gallery .

Event Partnership : O'Reilly is excited about the partnership between the museum and Makerfaire, encouraging others to visit both the Makerfaire and the museum during the weekend.

Summary Output Example:

Using a filtering approach based on average scores and standard deviation , a concise summary of O'Reilly's visit captures the essence of his experience in about 170 words , highlighting the museum's breadth, significance, and notable exhibits.

Alternative Summarization Approach

Overview : An alternative method for summarizing documents focuses on selecting the top N sentences (with N set to 5) to create a more concise summary. This results in a brief but informative distillation of the content.

Example Summary : A succinct version of Tim O'Reilly's visit to The Henry Ford Museum is around 90 words :

- O'Reilly visited The Henry Ford Museum in **Dearborn, MI** with Dale Dougherty and Marc Greuther.
- He initially expected it to focus on the auto industry but found it much more significant, referring to it as "the **Louvre of the Industrial Age** ."
- The museum chronicles industrial transformation, allowing visitors to spend a full day at both the museum and the **Makerfaire** .

Insights from Summarization

- **Visual Inspection** : Comparing the summarization to the full text reveals deeper insights into how effectively the key points are captured.
- **Output Format** : Adjusting the script to produce an HTML markup format allows for easy viewing in web browsers, aiding in the analysis of summarization results.

Example Code for HTML Output

- The provided code (Example 8-4) illustrates how to modify the output to create a simple HTML document for better visualization. It includes:
 - **HTML Template** : A basic structure for displaying the title and body content.
 - **Directory Creation** : Ensures the output folder exists for storing the marked-up summaries.
 - **Loading and Processing** : Reads blog data and updates each post with the generated summary.

This approach enhances the usability of the summarization results and facilitates analysis.

Storing Full Posts with Key Sentences Marked

Overview : You can enhance document analysis by storing the complete text of a post with key sentences highlighted. This allows for better visualization of important content.

Implementation Steps :

1. Mark Up Key Sentences :

- For each summary type (like **top n_summary** and **mean scored_summary**), create a marked-up version of the full content.
- Initialize the marked-up text with
`%s`
for HTML formatting.

2. Highlight Important Sentences :

- Loop through each summary type and replace each key sentence in the original text with a bold version using `%s` .
- This makes key sentences stand out in the final output.

3. Generate Output Files :

- Create a filename based on the post's title and summary type.
- Write the marked-up content into an HTML file.
- Notify the user of the file's location through standard error output.

Resulting Output : The final output consists of the full text, with important sentences highlighted in bold. This visual distinction allows for quick comparison of summarization techniques.

Example Insight : When examining the output, you can see the differences between summary approaches, such as identifying a significant sentence about "The machines are astonishing," which may not be as prominent in other summary types.

Next Steps

The following section will provide a discussion of Luhn's approach to summarization, expanding on the techniques used in the algorithm.

Analysis of Luhn's Summarization Algorithm

Overview : Luhn's algorithm identifies important sentences in a document based on the presence of frequently occurring words. Here are the key details:

1. Important vs. Unimportant Words :

- **Important Sentences** : The algorithm assumes that sentences containing frequently occurring words are significant.
- **Stopwords** : Common filler words (like "the," "and," "is") are typically excluded from analysis because they add little value. Custom stopword lists can enhance the algorithm by filtering out frequently used terms specific to a domain (e.g., "baseball" in a sports blog).

2. Top N Words :

- Select a reasonable value for **N** to identify the top **N** words for analysis.
- The assumption is that these words effectively represent the document's content. Sentences containing more of these words are deemed more descriptive.

3. Sentence Scoring :

- The function **score sentences** is crucial, as it scores each sentence based on the identified important words.
- **Clustering and Scoring** : Sentences are analyzed by clustering tokens based on a **distance threshold** . The highest score from any cluster in a sentence determines that sentence's final score.

Example Walkthrough :

- **Input Sentence :**

- ['Mr.', 'Green', 'killed', 'Colonel', 'Mustard', 'in', 'the', 'study', 'with', 'the', 'candlestick', '.']

- **Important Words List :**

- ['Mr.', 'Green', 'Colonel', 'Mustard', 'candlestick']

- **Cluster Threshold :**

- 3 (meaning clusters of tokens must be within a distance of 3 to be grouped).

Conclusion : Luhn's algorithm effectively filters out non-significant words and scores sentences to identify the most important content. It relies on clustering techniques and assumes that a higher density of important words in a sentence indicates greater significance. Further enhancements could include using TF-IDF to refine the scoring based on domain-specific vocabulary.

Intermediate Computation in Luhn's Summarization Algorithm

Cluster Detection :

- **Example Clusters Detected :**

- [['Mr.', 'Green', 'killed', 'Colonel', 'Mustard'], ['candlestick']]

- **Cluster Scores :**

- Scores calculated as [3.2, 1] , derived from the formula:
 - For the first cluster: $(4 \times 4) / 5 = 3.2$ $(4 \times 4) / 5 = 3.2$ $(4 \times 4) / 5 = 3.2$

- For the second cluster: $(1 \times 1) / 1 = 1$ $(1 \times 1) / 1 = 1$ $(1 \times 1) / 1 = 1$

Final Sentence Score :

- The **sentence score** is determined by the highest score from the detected clusters:
 - **Output** : 3.2 (max of [3.2, 1]).

Cluster Definition :

- A **cluster** consists of a sequence of words containing two or more important words, where each word is within a specified **distance threshold** from its nearest neighbor.
- In this example, a distance threshold of **3** was used for simplicity, allowing “Green” and “Colonel” to form a cluster.

Summary Extraction :

- Once sentences are scored, two approaches for summary extraction are implemented:
 1. **Statistical Threshold** : Filters sentences based on their scores relative to the **mean** and **standard deviation** .
 2. **Top N Sentences** : Returns a fixed number (N) of the highest-scoring sentences.

Considerations :

- Using the **Top N** method provides clarity on summary length, while the statistical method might yield more sentences than desired if scores are closely grouped.

Simplicity and Effectiveness :

- Luhn’s algorithm is straightforward to implement and effectively leverages frequently occurring words to summarize documents.
- However, it does not analyze deeper **semantic meanings** and relies solely on word frequency, which limits its sophistication.

Cost-Benefit Reflection :

- When considering more complex approaches, it’s crucial to weigh the effort required against the benefits of improved summarization. Sometimes, a basic heuristic like Luhn’s can suffice, while in other scenarios, a more advanced solution might be necessary. The challenge lies in accurately assessing the required effort for upgrades.

Entity-Centric Analysis: Understanding Data More Deeply

Key Concept :

- **Deeper Understanding** : Analytic methods that grasp the context and entities within data are often more effective than those that treat data points as mere symbols.

Entity Detection :

- A **core interpretation** of deeper understanding is the ability to **detect entities** within documents. This contrasts with **document-centric analysis** , which typically relies on keyword searches.

Example :

- Technologies like **WolframAlpha** exemplify this approach. When you search for "Tim O'Reilly," the results indicate an understanding that the query is about a **person** , rather than just returning documents containing those keywords.

User Experience :

- The user experience is significantly enhanced when search results align with user expectations, providing more relevant and contextual information rather than just a list of documents.

Conclusion :

- By focusing on entities and their relationships, analytic tools can deliver results that are more meaningful and user-friendly, highlighting the importance of moving beyond basic keyword analysis.

Overview :

- This section discusses how to extract entities from documents, which can be used for various analytic purposes. Although the full potential of **entity-centric analysis** is not explored here, we present a method for extracting these entities.

Noun Extraction :

- A simple and effective approach is to **extract all nouns and noun phrases** from the document. This assumes that these elements qualify as entities of interest, which is a reasonable starting point for entity-centric analysis.

Entity Extraction Process :

- **Entity Extraction** : The process of identifying entities within a text, often referred to as **entity extraction** in data mining.
- The **Penn Treebank Tagging** convention is used, where any tag starting with 'NN' indicates a noun or noun phrase.

Example Code :

- The provided code (Example 8-5) uses the **NLTK** library to extract entities:
 1. **Tokenization** : The text is first divided into sentences and then into words.
 2. **POS Tagging** : Each token is tagged with its part of speech (POS).
 3. **Entity Chunking** : The code identifies sequences of tokens that are nouns or noun phrases:
 - If the current token's POS tag matches the previous one and starts with 'NN', it is added to the current entity chunk.
 - If it doesn't match, the current chunk is saved, and a new chunk begins.

Summary :

- This method provides a foundational technique for entity-centric analysis by focusing on nouns and noun phrases, setting the stage for deeper exploration of the entities within a document.

Extracting and Analyzing Entities

Overview :

- This section explains how to manage entity extraction to ensure accuracy and track frequency in documents.

Handling Duplicates :

- When adding **current** `entity_chunk` to the list of entities, it's essential to note that it might contain duplicates. Thus, **frequency analysis** becomes necessary to accurately count occurrences.

Storing Entities :

- Entities are stored in a dictionary within the post, allowing for easy indexing and frequency tracking:
 - Each entity is stored alongside its count, incrementing the count if it appears again.

Displaying Results :

- The code example displays **title-cased entities** (e.g., proper nouns) along with their frequencies:
 - Proper nouns are identified using the `istitle()` method, which checks if the entity begins with an uppercase letter.

Using NLTK for Named Entity Recognition :

- The NLTK library offers the **`nltk.batch`** `ne_chunk` function, which can extract named entities from POS-tagged tokens. While this tool is available, results may vary based on the underlying models, and further improvements to the implementation are not covered here.

Sample Output :

- Example 8-6 provides a meaningful output that shows extracted entities and their frequencies, which could inform tagging for a blogging platform.
- For larger datasets, visualizing the results through a **tag cloud** could enhance data interpretation.

Summary:

- This process facilitates efficient entity extraction and frequency analysis, setting the groundwork for more complex analyses and applications in natural language processing (NLP).

Analyzing Entity Extraction

Extracted Entities : The following entities were identified along with their frequencies:

- **Ford** (2)
- **Santa Rosa** (1)
- **Dearborn** (1)
- **Makerfaire** (2)
- **Berlin** (1)
- **Marc** (2)
- **Rome** (1)
- **Henry Ford** (1)
- **Louvre** (2)
- **Detroit** (2)
- **St. Petersburg** (1)
- **Florence** (1)
- **Luther Burbank** (2)
- **Dale Dougherty** (1)
- **Make** (1)

Analysis Techniques:

1. Lexical Characteristics :

- Simply analyzing **capitalization** could identify some terms, but this method might miss important nouns and noun phrases that are not capitalized (e.g., “chief curator,” “locomotives,” “lightbulbs”).
- Case is a useful feature, but focusing solely on it can overlook significant entities that contribute meaning.

2. Value of Entities :

- The list of extracted entities, while not summarizing the text effectively, provides valuable semantic insights. These entities represent people, places, things, or ideas, which are central to the content.
- Most terms have low frequencies but are meaningful due to their grounded relevance.

Further Analysis:

• Subject-Verb-Object Triples :

- Expanding the analysis to include **verbs** could create triples (subject-verb-object) that detail interactions among entities.
- This would help visualize the relationships between entities and allow for quicker comprehension of documents.

Visualization Potential:

- Object graphs derived from multiple documents could illustrate relationships and interactions, aiding in understanding larger corpora and addressing **information overload** .

Challenges:

- While promising, creating and analyzing such object graphs is complex and presents significant challenges, making it a demanding area of research.

Conclusion:

- This entity-centric approach enhances the understanding of text beyond mere frequency analysis, focusing on the semantic significance of entities and their relationships.

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Extracting Predicate-Object Tuples in Natural Language Processing

Concept of Tuples :

- **Predicate-Object Tuples** : These are structured as ('Subject', 'Verb', 'Object'), representing actions and their participants. For example, ('Mr. Green', 'killed', 'Colonel Mustard').

Challenges in Real-World Data:

- **Complexity of POS-Tagged Data** : In practice, POS (Part-of-Speech) tagging from tools like NLTK can be complex. An example sentence from a blog is:
"This morning I had the chance to get a tour of The Henry Ford Museum in Dearborn, MI, along with Dale Dougherty, creator of Make: and Makerfaire, and Marc Greuther, the chief curator of the museum."
 - **POS Tags Example** :
 - Example tags from the sentence:
 - [('This', 'DT'), ('morning', 'NN'), ('I', 'PRP'), ('had', 'VBD'), ('the', 'DT'), ('chance', 'NN'), ('to', 'TO'), ('get', 'VB'), ('a', 'DT'), ('tour', 'NN'), ...]
- **Difficulty in Extraction** :
 - A simple triple like ('I', 'get', 'tour') fails to capture all involved parties, like Dale Dougherty and Marc Greuther. The sentence structure is complex, making it difficult for even advanced systems to generate meaningful triples.

Realistic Expectations:

- **Understanding Complexity** : The complexity of NLP (Natural Language Processing) tasks like extracting triples should be recognized. While challenging, the effort can yield significant insights.

Entity-Centric Analysis:

- **Value of Entities** : Focusing on extracting **entities** (nouns and noun phrases) can provide a rich basis for analysis. You can produce meaningful interactions between entities using simplified relationships.
- **Using Sentences as Context** : You can collect entities from each sentence, allowing for analysis of interactions in context. This method facilitates understanding relationships without delving into the complexities of full triples.

Conclusion:

- **Extracting Entities** : While generating detailed predicate-object tuples can be complex, extracting entities and analyzing their interactions is a practical and effective approach in NLP, providing valuable insights into the data.

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Extracting Interactions Between Entities

Overview : This example demonstrates how to extract interactions between entities within text using Natural Language Processing (NLP) techniques.

Key Components of the Code:

1. Imports :

◦ Libraries Used :

- `sys` : For system-specific parameters and functions.
- `nltk` : The Natural Language Toolkit for text processing.
- `json` : For reading JSON data.

2. Function: `extract_interactions(txt)` :

- **Purpose** : To identify and extract interactions between entities in a given text.

3. Process :

◦ Tokenization :

- The text is split into sentences and then into words using `nltk.tokenize` .

◦ POS Tagging :

- Each word is tagged with its part of speech (POS) using `nltk.pos_tag`.

4. Entity Detection :

- **Chunking Entities :**
 - The code iterates over the POS-tagged tokens to create **chunks of entities** (nouns).
 - It uses a list called `all_entity_chunks` to collect these entities based on their POS tags.
- **Interaction Detection :**
 - If a sentence contains more than one entity, it's considered an **interaction** and is added to `entity_interactions`.

5. Return Value :

- The function returns a dictionary containing:
 - `entity_interactions` : A list of interactions for each sentence.
 - `sentences` : The original sentences from the text.

Main Execution Block:

- **Reading Blog Data :**
 - The script reads JSON data containing blog posts from a specified file.
- **Processing Each Post :**
 - For each blog post, it updates the post with extracted interactions and prints the title.

Conclusion:

This script provides a practical approach to analyzing text by identifying how entities interact within sentences, enabling deeper insights into the relationships presented in the text.

Analyzing Entity Interactions Output

Overview : The output from the previous code highlights the challenges of analyzing unstructured data, showing that the results can be messy and complex.

Key Points from the Output:

1. Output Structure :

- Each title is printed followed by a line of dashes.
- For each interaction detected, entities are listed, separated by semicolons.

2. Sample Results :

- The output consists of various entities mentioned in the text. For example:
 - **Entities Identified** : "morning; chance; tour; Henry Ford Museum; Dearborn; MI; Dale Dougherty; creator; Make; Makerfaire; Marc Greuther; chief curator"
 - Other results include references to people, places, and concepts related to the text, indicating multiple entities mentioned in each sentence.

3. Nature of Unstructured Data :

- **Messiness** : The output demonstrates the inherent messiness of analyzing unstructured data. There can be a lot of irrelevant or extraneous information mixed in with valuable insights.
- **Noise** : Some results contain noise, making them less intelligible. However, achieving completely noise-free results is often unrealistic due to the complexity of natural language.

4. Effort vs. Quality :

- Achieving high-quality, noise-free results requires significant effort and may be impossible in many cases. The complexity of natural language and the limitations of tools like NLTK contribute to this challenge.
- **Domain Knowledge** : If you have specific knowledge about the data's context, you might develop effective heuristics to improve analysis without excessively filtering out useful information.

Conclusion:

While analyzing entity interactions provides meaningful insights, it's important to recognize that results will likely contain some noise. Striving for intelligibility and utility in the results is key, even if complete clarity is unattainable.

Entity Interaction Analysis and Markup

Overview : Analyzing entity interactions helps capture valuable information, but challenges exist regarding potential information loss. A clearer presentation can enhance understanding.

Key Concepts:

1. Information Loss :

- Extracting interactions may lead to **information loss** , which is problematic.
- The challenge lies in balancing the extraction process while retaining meaningful content.

2. Value of Interactions :

- Despite potential loss, the interactions provide a **"gist"** of the text.
- For instance, the phrase "morning; chance; tour; Henry Ford Museum; Dearborn; MI; Dale Dougherty; creator; Make; Makerfaire; Marc Greuther; chief curator" reflects key elements of the original sentence.

3. Visual Skimming :

- Displaying results in a visually accessible format is beneficial. This allows for easier inspection and interpretation of the extracted data.

4. Modification for Markup :

- A simple adjustment to the script can enhance the output by presenting entities in a bold format, improving readability and comprehension.
- **HTML Template** : The script utilizes an HTML template to structure the output. This format includes the title and body content for web presentation.

Example Code Modification:

- The modified script (referred to as `blogs_and_nlp_extract_interactions_markedup_output.py`) allows for:
 - **Creating Output Directory** : If the output directory doesn't exist, it creates one.
 - **Markup Creation** : The script prepares a marked-up version of the data where entities are highlighted, making the information more accessible.

Conclusion:

While analyzing entity interactions can lead to some information loss, enhancing the presentation of these interactions helps maintain the integrity of the data. By utilizing markup and visual formats, one can more effectively convey the essence of the original content.

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Markup and Visualization of Entity Interactions

Process Overview : This section describes how to enhance text analysis by highlighting entity interactions and creating an HTML output for easier reading and interpretation.

Key Steps:

1. Sentence Processing :

- For each **sentence** in the text, the script retrieves the sentence using its index.
- It identifies **terms** that represent entities and replaces them in the sentence with a bold format for emphasis.

2. HTML Output Creation :

- The modified sentences are stored in a list called `markup` .
- Each post generates an HTML file named after the post's title, with a `.entity_interactions.html` extension.
- The final HTML includes the title and all sentences with highlighted entities.

3. File Writing :

- The script writes the generated HTML content to a file within a designated output directory, ensuring the file is encoded in UTF-8.
- A message is printed to the console indicating that the data has been written successfully.

Considerations for Further Analysis:

- **Extended Interaction Analysis :**
 - For larger text bodies, it's beneficial to analyze sets of interactions to uncover **co-occurrences** between entities.
- **Visualization Tools :**
 - The use of **Graphviz** or **Protovis** can help visualize the interactions graphically, representing entities and their relationships in a more digestible format.
 - A provided example from a GitHub repository illustrates how to visualize interactions, which can serve as a useful reference.

Conclusion:

Highlighting entity interactions in the output significantly enhances the clarity of the data, allowing for easier scanning of key concepts. Further analyses and visualizations can deepen understanding and reveal patterns in interactions across larger datasets.

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Quality of Analytics in Text Mining

Understanding Analytics Quality : To assess the effectiveness of analytics, especially in text mining , it's crucial to measure the quality of your results. As you refine your data extraction algorithms, knowing their performance on larger datasets or different document types is essential.

Key Concepts:

1. Performance Evaluation :

- Manually inspecting results from a small set of documents can help fine-tune your algorithm, but this method may not accurately predict performance on larger or varied datasets.
- **Automated evaluation** methods are needed for broader assessments.

2. Golden Set Creation :

- Randomly sample documents to create a **"golden set"** of critical entities. This set serves as a benchmark to evaluate your algorithm's effectiveness.
- By comparing your algorithm's output to this golden set, you can gauge its accuracy.

3. Statistical Methods :

- To enhance your evaluation, compute the **sample error** and use **confidence intervals** . These statistical tools allow you to predict the true error rate with a level of confidence.

Measuring Accuracy:

1. F1 Score :

- A widely used metric for accuracy in analytics is the **F1 score** , which balances two key measures: **precision** and **recall** .
- The F1 score is defined as the **harmonic mean** of precision and recall. This means it provides a single score that considers both false positives and false negatives in your results.

2. Precision and Recall :

- **Precision** measures the accuracy of the entities extracted (true positives divided by the total predicted positives).
- **Recall** measures the algorithm's ability to find all relevant entities (true positives divided by the total actual positives).

Conclusion:

Quantifying the quality of analytics in text mining is vital for improving algorithms. By creating a golden set and applying statistical measures like the F1 score, you can effectively assess and enhance your text mining processes.

Understanding Precision, Recall, and F1 Score in Analytics

Key Metrics : In text mining, two important metrics are precision and recall , which help evaluate the performance of an algorithm in identifying entities.

Definitions:

- **True Positives (TP)** : Correctly identified entities.
- **False Positives (FP)** : Incorrectly identified terms that are not entities.
- **True Negatives (TN)** : Terms that were correctly not identified as entities.
- **False Negatives (FN)** : Entities that were not identified when they should have been.

Precision:

- **Precision** measures the **exactness** of the algorithm and is calculated as: $\text{Precision} = \frac{TP}{TP + FP}$
- A precision of **1.0** (or 100%) indicates that there are **no false positives** , meaning every identified term is correct.

Conversely, if false positives are high relative to true positives, precision approaches **0**.

Recall:

- **Recall** measures the **completeness** of the algorithm and is defined as: $\text{Recall} = \frac{TP}{TP + FN}$
- A recall of **1.0** indicates that there are **no false negatives**, meaning all relevant entities were identified. As false negatives increase, recall approaches **0**.

F1 Score:

- The **F1 score** combines precision and recall into a single metric:
 - It yields **1.0** when both precision and recall are perfect and approaches **0** when both are poor.
- Typically, there is a trade-off between precision and recall—improving one may decrease the other.

Example:

Consider the sentence: "Mr. Green killed Colonel Mustard in the study with the candlestick."

- **Identified Entities** : "Mr. Green", "Colonel Mustard", "study", "candlestick"
- **Analysis** :
 - **TP** = 4 (correct entities identified)
 - **FP** = 0 (no incorrect identifications)
 - **TN** = 5 (terms not identified that are not entities)
 - **FN** = 0 (no missed entities)

In this case:

- **Precision** = 1.0 (perfect)
- **Recall** = 1.0 (perfect)
- **F1 Score** = 1.0 (perfect)

Additional Calculation:

If the algorithm incorrectly identified "Colonel" and "Mustard" separately, instead of as "Colonel Mustard," this would affect precision and recall. Evaluating different values helps understand the impact on performance.

Conclusion:

Precision, recall, and F1 score are crucial for assessing the effectiveness of text mining algorithms. Understanding these

Overview of Advanced Natural Language Processing (NLP) Techniques

Technology Stacks in NLP :

- Many successful **commercial NLP applications** utilize **advanced statistical models** with **supervised learning algorithms** .
- A **supervised learning algorithm** involves providing a model with **training samples** in the format:
[(input1, output1), (input2, output2), ..., (inputN, outputN)] \text{[(input1, output1), (input2, output2), ..., (inputN, outputN)]} [(input1, output1), (input2, output2), ..., (inputN, outputN)]
- The goal is for the model to **predict outputs** based on new inputs with good accuracy.

Challenges:

- A key challenge is ensuring that the model can **generalize** well to **unseen data** .
- If a model performs well on training data but poorly on new data, it is said to suffer from **overfitting** .

Cross-Validation:

- To measure a model's effectiveness, **cross-validation** is commonly used:
 - A portion (e.g., **one-third**) of the training data is set aside for **testing** .
 - The rest is used solely for **training** the model, allowing for a more reliable assessment of its performance.

Closing Remarks:

- This chapter covered the **fundamentals of unstructured data analytics** and demonstrated how to leverage **NLTK** for extracting entities from text.
- The field of **computational linguistics** is still developing, and solving NLP challenges for widely spoken languages remains a significant undertaking.
- To enhance performance and quality beyond basic capabilities, delving into **academic literature** and advanced techniques is encouraged, despite the complexity involved.

Key Takeaway:

Understanding and applying advanced NLP techniques, such as supervised learning and cross-validation, are essential for developing effective language processing systems.

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Expanding on NLP Techniques with NLTK

Word-Stemming :

- Consider using **NLTK's word-stemming tools** to create tuples in the format: (entity , stemmed predicate , entity) (`\text{entity}`, `\text{stemmed predicate}`, `\text{entity}`) (entity , stemmed predicate , entity)
- This approach builds on the code from **Example 8-7** and enhances your analysis by reducing words to their root forms.

Using WordNet :

- Explore **WordNet** , a lexical database that provides additional meanings and relationships for words.
- This can enrich your understanding of the items in your tuples, offering deeper insights into their contexts.

Integrating NLP with Commenting APIs :

- If you have extra time, look into popular commenting APIs like **DISQUS** .
- Try to apply the NLP techniques discussed in the chapter to analyze and improve comment streams for blog posts.

Creating a WordPress Plugin :

- Consider developing a **WordPress plugin** that intelligently suggests tags based on extracted entities from draft blog posts.
- This project can be a rewarding way to apply what you've learned while enhancing your blogging experience.

Key Takeaways:

Engaging with these additional tools and projects can deepen your understanding of NLP and enhance your practical skills in applying these techniques effectively.

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Chapter 9: Facebook - The All-in-One Wonder

Overview of Facebook :

- **Facebook** boasts over **500 million users** , offering a wide range of functionalities, including:
 - Updating public statuses.
 - Exchanging messages similar to email.
 - Engaging in real-time chat.
 - Organizing and sharing photos.
 - "Checking in" to physical locations.
- By the end of 2010, Facebook surpassed Google as the **most visited website** , highlighting its immense popularity and user engagement.

Data Mining Potential :

- The large user base creates an abundance of interesting data for analysis.
- In this chapter, we will leverage **Facebook's powerful APIs** to:
 - Identify your most connected friends.
 - Cluster friends based on shared interests.
 - Monitor trending topics within your social network.

Using Facebook APIs :

- We will begin with a brief overview of common **Facebook APIs** before moving on to practical applications.
- The techniques discussed in previous chapters can also be applied to Facebook data, thanks to its rich and diverse platform.

Exploration and Privacy Considerations :

- Although this chapter won't cover every possible application, there's vast potential for data mining and analysis on Facebook.
- When developing applications, it's crucial to respect user privacy and regularly review **Facebook's developer principles and policies** to avoid complications when deploying your applications.

Key Takeaways:

- Facebook is a powerful platform for social data analysis.
- Utilizing its APIs can reveal insights into social connections and trends.
- Always prioritize user privacy and adhere to Facebook's guidelines in your applications.

Tapping into Your Social Network Data

Overview : This section guides you through completing Facebook's OAuth 2.0 flow for a desktop application to obtain an access token . It focuses on data-gathering exercises rather than building a full Facebook application.

Key Points :

- **No Application Development** : The chapter won't cover how to build a Facebook application, as this requires knowledge of a server platform (like **Google App Engine (GAE)**). However, a GAE version of the scripts used here can be found [here](#) . This can serve as a starting point for future development.

Steps to Acquire an Access Token

1. Create a Facebook Account :

- If you don't have one, sign up at facebook.com .

2. Install the Developer Application :

- Go to [Facebook Developers](#) and follow the prompts to install the Developer application.

3. Set Up Your Application :

- Once the Developer application is installed, click on the “ **Set Up New Application** ” button to create your application.

Visual Aids :

- Refer to **Figure 9-2** for visual guidance on these steps.

Summary:

- This section provides essential steps for accessing Facebook data through OAuth 2.0, facilitating the acquisition of an access token for further data gathering.

Setting Up a New Facebook Application

Figure 9-2 Overview : This figure illustrates the steps to set up a new application on Facebook.

1. Access the Developer Portal :

- Visit [Facebook Developers](#).
- Click the button to **set up a new application**.

2. Complete the Application Setup :

- Fill out the dialog box that prompts you to:
 - **Name your app**.
 - Acknowledge **terms of service**.

3. Application List :

- After setting up, your application will be displayed in the list of applications.

4. Application Settings :

- Access your app's settings to find important details, including:
 - **OAuth 2.0 app ID**.
 - **App secret**.

Key Concepts :

- **OAuth 2.0** : A protocol for authorization that allows secure access to Facebook APIs.
- **App ID and Secret** : Unique identifiers for your application, crucial for accessing Facebook's data.

Summary:

Figure 9-2 provides a visual step-by-step guide for creating a Facebook application, highlighting the key actions required to complete the setup and access necessary credentials.

Setting Up Your Facebook Application for OAuth 2.0

1. Complete Security Check :

- After passing the security check, your app will receive an **ID** and **secret** . These are essential for implementing **OAuth 2.0** .

2. Configure Web Site Settings :

- Fill out the form with your app's **Web Site settings** :
 - **Site URL** : Enter the URL where your app will be hosted.
 - **Site Domain** : Use the same domain as the Site URL.
- Proper configuration is crucial; incorrect entries can cause errors during the OAuth process.

3. Accessing Your Development Application :

- If you need to return to your app setup, go to [Facebook Developers](#) (login required).

Authentication and Access Token Retrieval

• Script for Access Token :

- The next step is to write a script that manages authentication and retrieves an **access token** to access Facebook APIs.
- The process is simpler than for Twitter and LinkedIn:
 - A web browser will open.
 - Sign in to your Facebook account.
 - Copy the **access token** presented and paste it into a prompt to save it for future API requests.

Example Script: Getting an OAuth 2.0 Access Token

• Basic Code Overview :

- The example script, `facebook_login.py` , demonstrates the OAuth 2.0 flow for a desktop application. It includes:
 - **CLIENT ID** : Obtain this from your Facebook application's settings.
 - **REDIRECT URI** : Set to a predefined URL for handling responses.

Additional Notes:

- For detailed guidance, review Facebook's authentication documentation. The flow in the example for desktop applications is simpler than for web apps.

Extended Permissions in Facebook API

• Purpose of Extended Permissions :

- These permissions allow applications to access a wide range of user and friend data on Facebook,

enhancing functionality and user interaction.

List of Extended Permissions:

1. User Data :

- `user about_me` : Access to user's profile information.
- `user birthday` : Access to user's birthday.
- `user education_history` : Access to user's education background.
- `user events` : Access to user's events.
- `user groups` : Access to user's groups.
- `user hometown` : Access to user's hometown.
- `user interests` : Access to user's interests.
- `user likes` : Access to user's likes.
- `user location` : Access to user's current location.
- `user notes` : Access to user's notes.
- `user online_presence` : Access to user's online status.
- `user photos` : Access to user's photos.
- `user relationships` : Access to user's relationships.
- `user religion_politics` : Access to user's religion and political views.
- `user status` : Access to user's status updates.
- `user videos` : Access to user's videos.
- `user website` : Access to user's personal website.
- `user work_history` : Access to user's work history.
- `email` : Access to user's email address.

2. Friends' Data :

- Each user-related permission has a corresponding permission for friends, e.g.:
 - `friends about_me`
 - `friends birthday`
 - `friends education_history`
 - and so on for all user permissions listed.

3. Stream and Check-ins :

- `read friendlists` : Access to friends list.
- `read requests` : Access to friend requests.
- `read stream` : Access to user's news feed.
- `user checkins` : Access to user's check-in locations.
- `friends checkins` : Access to friends' check-ins.

Constructing the Authorization Request:

• Arguments for OAuth Authorization :

- `client_id` : Your application's ID.
- `redirect_uri` : The URI to which the user will be redirected after authorization.
- `scope` : A comma-separated string of the extended permissions requested.
- `type` : Set to `'user_agent'` to specify the method of authentication.
- `display` : Set to `'popup'` to display the authorization request in a popup window.

Opening the Authorization URL:

- The final step involves constructing the URL to open in the web browser, which initiates the OAuth authorization

process.

This setup allows the application to request and gain access to extensive user and friends' data on Facebook, provided that the user consents to share this information.

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Accessing Facebook Data: Storing Access Tokens

1. Constructing the Authorization URL :

- Use the `urllib.urlencode(args)` function to create a URL for accessing Facebook's API with the necessary arguments.

2. Storing Access Tokens :

- After logging in, the application prompts the user to enter their **access token** . This token is crucial for making authorized API calls.
- To make future API calls easier, the access token can be stored locally:
 - Check if the **'out'** directory exists; if not, create it.
 - Save the access token in a file named **'facebook.access token '** within the **'out'** directory.

3. Output Confirmation :

- A message confirms that the access token has been stored successfully:
 - **"Access token stored to local file: 'out/facebook.access token '"**

Understanding Extended Permissions

1. What Are Extended Permissions? :

- When the application first requests access, it may ask for **extended permissions** , allowing it to access a broader range of user data beyond the basic profile information.

2. Default Permissions :

- By default, Facebook applications can only access limited user information, such as:
 - **Name**
 - **Gender**
 - **Profile picture**
- To access more detailed information, such as friends' likes or activities, explicit permissions must be granted.

3. Difference Between User Access and API Access :

- Users may see certain details about their friends on **facebook.com** that are not available through the API unless the application has the necessary permissions.
- When logged into facebook.com, Facebook manages data access directly. In contrast, as a developer, you must explicitly request access through your application.

4. Implications of Not Requesting Permissions :

- If an app attempts to access data without having requested the necessary extended permissions, it may

return **empty data objects** rather than an error message.

Conclusion

- Understanding how to handle access tokens and the implications of extended permissions is essential for effectively utilizing Facebook's API. This knowledge ensures that applications can access the desired data while adhering to Facebook's privacy and access policies.

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Accessing Data Permissions on Facebook

1. Permission Dialog Overview :

- When an application requests access to a user's Facebook data, a dialog appears to inform the user about the permissions being requested.
- This dialog visually represents the **scope of access** the application seeks, often referred to as "**The Kitchen Sink**" because it requests a wide range of data.

2. Types of Data Requested :

- The permissions may include access to various personal information and activities, such as:
 - Profile details (name, gender, profile picture)
 - Friends' information (likes, activities)
 - User-generated content (posts, comments)

3. User Awareness :

- Users are prompted to review and **explicitly grant permissions** to ensure they understand what data the application will access.
- This transparency helps users make informed decisions about their data privacy.

4. Importance of Permissions :

- Without granted permissions, the application will be unable to access certain data, potentially resulting in empty data objects instead of the expected information.

Conclusion

- Understanding the permission dialog is crucial for developers to ensure their applications are transparent about data access, which enhances user trust and complies with Facebook's privacy policies.

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Understanding Facebook's Data Access and APIs

1. Evolving Documentation :

- Facebook's documentation is constantly changing and may not cover all details regarding **extended permissions** .
- For example, to access **friends' religious or political information** , those friends must also have your app installed and grant permission.

2. Access Tokens :

- Once you have an access token with the necessary permissions, you can start exploring and utilizing your data.

Facebook's Query APIs

1. Complex Ecosystem :

- The Facebook developer environment is intricate and continually evolving, with advanced **privacy controls** .

2. Types of APIs :

- Facebook offers a variety of APIs:
 - **REST APIs** : Standard interface for accessing data.
 - **Facebook Query Language (FQL)** : An SQL-like language for querying data.
 - **Graph API** : A primary interface for interacting with the Facebook social graph.
 - **Open Graph Protocol (OGP)** : Allows web pages to be treated as objects in the social graph by adding **RDFa** metadata.

3. Graph API Objects :

- The Graph API supports several object types, each serving different purposes:
 - **Album** : Represents a photo album.
 - **Application** : Refers to a registered app on the Facebook platform.
 - **Checkin** : Records a location check-in via Facebook Places.
 - **Event** : Details a Facebook event.
 - **Group** : Refers to a Facebook group.
 - **Link** : Represents a shared link.
 - **Note** : A Facebook note.

Conclusion

- Familiarizing yourself with Facebook's evolving permissions and APIs is crucial for effectively leveraging the platform's data while respecting user privacy.

Facebook Graph API Object Types

1. Object Types :

- The **Graph API** supports various object types, each with specific functions:
 - **Page** : Represents a Facebook page.
 - **Photo** : An individual photo.
 - **Post** : A single entry in a user's feed.
 - **Status Message** : A status update on a user's wall.
 - **Subscription** : A subscription from an application for real-time updates on an object type.
 - **User** : Refers to a user profile.
 - **Video** : An individual video.

2. Graph API Reference :

- Contains comprehensive documentation on each object type, detailing properties and connections that can be expected.

Open Graph Protocol (OGP)

1. Turning Web Pages into Objects :

- The Open Graph protocol allows web pages to be represented as objects, enhancing their machine-readable format. For example, the IMDB page for "The Rock" can be transformed into an OGP object through metadata in an XHTML document.

Sample RDFa Example :

html Copy code `< html xmlns:og = "http://ogp.me/ns#" > < head > < title > The Rock (1996) < meta property = "og:title" content = "The Rock" /> < meta property = "og:type" content = "movie" /> < meta property = "og:url" content = "http://www.imdb.com/title/tt0117500/" /> < meta property = "og:image" content = "http://ia.media-imdb.com/images/rock.jpg" />`

2. Potential of OGP :

- OGP can enable a web page to be represented unambiguously, supporting the vision for a **semantic web** .

3. Considerations :

- While exploring OGP, it's important to be innovative yet cautious, as the protocol is still evolving. There are ongoing discussions regarding its standards and capabilities, with some limitations due to it being primarily a **single-vendor effort** .

Conclusion

- The Graph API and Open Graph protocol present powerful tools for interacting with Facebook data and enhancing web pages for better integration and understanding within the semantic web. Understanding the object types and metadata usage is crucial for leveraging these technologies effectively.

Understanding the Open Graph Protocol (OGP) and Graph API

1. Current Status of OGP :

- The **Open Graph Protocol (OGP)** is still evolving and resembles more of a unique concept ("snowflake") than a standardized format. However, it holds significant potential for future development and innovation.
- The concept of the **semantic web** will be explored further in Chapter 10, highlighting its vast possibilities.

2. Graph API Basics :

- The **Graph API** allows users to access Facebook data by substituting an object's ID in the URL format: `http(s)://graph.facebook.com/ID` .
- For example, accessing `http://graph.facebook.com/http://www.imdb.com/title/tt0117500` retrieves information about the film "The Rock."

3. Sample Response from the Graph API :

- A typical response from the Graph API includes fields such as: json Copy code

```
{ "id" : "114324145263104" , "name" : "The Rock (1996)" , "picture" : "http://profile.ak.fbcdn.net/hprofile-ak-snc4/hs344.snc4/41581...jpg" , "link" : "http://www.imdb.com/title/tt0117500/" , "category" : "Movie" , "description" : "Directed by Michael Bay. With Sean Connery, Nicolas Cage, ..." , "likes" : 3 }
```
- The fields in the response correspond to **meta tags** on the IMDb page, emphasizing the rich metadata provided by OGP.

4. Requesting Additional Metadata :

- You can request extra metadata by appending the query string `metadata=1` to your request.
- For example, `https://graph.facebook.com/114324145263104?metadata=1` yields a response with additional details about the object.

5. Sample Response with Metadata :

- A response with the optional metadata might include: json Copy code

```
{ "id" : "118133258218514" , "name" : "The Rock (1996)" , "picture" : "http://profile.ak.fbcdn.net/hprofile-ak-snc4/...s.jpg" , "link" : "http://www.imdb.com/title/tt0117500" , "category" : "Movie" , "website" : "http://www.imdb.com/title/tt0117500" , "description" : "Directed by Michael Bay. With Sean Connery, Nicolas Cage, ..." }
```

Conclusion

- The Graph API is a powerful tool for accessing and querying Facebook data. By utilizing OGP and the Graph API, developers can tap into rich metadata to create engaging applications and enhance user experiences.

Exploring Metadata and Graph API Connections

1. Understanding Metadata :

- The **metadata** section in a Graph API response includes **connections** to related data points.

- For example, the connections for a specific movie page might include:
 - **Feed** : `http://graph.facebook.com/http://www.imdb.com/title/tt0117500/feed`
 - **Posts** : `http://graph.facebook.com/http://www.imdb.com/title/tt0117500/posts`
 - **Photos** : `http://graph.facebook.com/http://www.imdb.com/title/tt0117500/photos`
 - Each of these links allows you to explore different aspects of the movie's presence on Facebook.

2. Data Fields :

- The metadata also defines specific **fields** , such as:
 - **id** : The unique identifier for the page (publicly available).
 - **name** : The name of the page (publicly available).
 - **category** : The category of the page (publicly available).
 - **likes** : The number of users who like the page.

3. Crawling Connections :

- The links provided in the **connections** allow you to navigate through related data. For instance, following the **photos** link can show you images associated with the movie, and you can further explore who posted them or the comments made about them.
- This interconnected structure makes it easy to discover additional relevant information.

4. Your Role in the Graph :

- You are also considered an **object** within the Facebook graph. By replacing the movie URL with your own Facebook ID or username, you can see your own data and connections.
- This personal exploration emphasizes your centrality in your social network.

5. Using the Graph API :

- Facebook provides an official **Python SDK** for the Graph API. You can install it using: `bash Copy code easy install facebook-python-sdk`
- This SDK simplifies the process of implementing the OAuth authentication flow and building applications that interact with Facebook data.

Conclusion

- The Graph API is a powerful tool for accessing and exploring interconnected data on Facebook. By understanding metadata, connections, and your role within the graph, you can leverage this API to build meaningful applications that tap into social data.

Using the Graph API with Standalone Scripts

1. GraphAPI Class Overview :

- The **GraphAPI class** (defined in `facebook.py`) provides methods to interact with Facebook's Graph API.
- You can utilize this class in **standalone scripts** instead of building a full Facebook app.

2. Key Methods :

- `**get object (self, id, args)` : Retrieves a single object by its ID.
 - Example: `get object ("me", metadata=1)` fetches your user profile with metadata.
- `**get objects (self, id, args)` : Retrieves multiple objects.

- Example: `get_objects(["me", "some_other_id"], metadata=1)` fetches details for you and another user.
- `**get_connections(self, id, connection_name, args)`: Retrieves connections associated with an object.
 - Example: `get_connections("me", "friends", metadata=1)` gets your friends list with additional metadata.
- `request(self, path, args=None, post_args=None)`: Sends a request to a specific API path.
 - Example: `request("search", {"q": "programming", "type": "group"})` searches for groups related to programming.

3. API Rate Limits :

- Unlike some other social networks, Facebook does not have clearly published **API rate limits**.
- Although the API is generally generous, it's essential to **design your application** to minimize API calls and handle errors gracefully.
- For guidance, check developer forums for discussions on best practices.

4. Using Metadata :

- The most common keyword argument is **metadata=1**, which returns connections along with the object details.
- This is crucial for understanding relationships and additional data related to the objects you query.

5. Example of Querying Groups :

- Example 9-5 demonstrates how to query for **programming groups** using the Graph API.
- The script reads the **access token** from a file and handles command-line input.

Conclusion

- Utilizing the GraphAPI class in standalone scripts allows for efficient interactions with Facebook's data. Understanding key methods and their functionalities, as well as being aware of rate limits and metadata usage, is vital for effective application development.

Querying Facebook Groups Using the Graph API

1. Setting Up Access :

- The **access token** is retrieved from command-line arguments: python Copy code `ACCESS_TOKEN = sys.argv[1] Q = sys.argv[2]`
- If the access token cannot be found or parsed, the script prompts the user to log in and obtain it.

2. Initialization :

- A limit is set for the number of results per query:
 - **LIMIT = 100**
- The **GraphAPI instance** is created using the access token: python Copy code `gapi = facebook.GraphAPI(ACCESS_TOKEN)`

3. Searching for Groups :

- An empty list, `group_ids`, is initialized to store the IDs of the groups found.
- A **while loop** is used to search for groups that match the query term (`Q`):

- The search request is made using: `python Copy code results = gapi.request('search' , { 'q' : Q, 'type' : 'group' , 'limit' : LIMIT, 'offset' : LIMIT * i, })`
- The loop continues until no more results are found or groups stop containing the search term in their names:
 - Groups are filtered by checking if the name contains "programming".

4. Breaking the Loop :

- If no IDs are found in the results, the loop exits: `python Copy code if len (ids) == 0 : break`

5. Handling No Results :

- If no group IDs are collected, the script prints "No results" and exits: `python Copy code if not group_ids : print 'No results' sys.exit()`

6. Retrieving Group Details :

- The details for the identified groups are fetched using: `python Copy code groups = gapi.get_objects (group_ids , metadata= 1)`

7. Counting Group Members :

- For each group, the script retrieves member information:
 - The FQL documentation notes that groups with over 500 members may return only a random subset of members.
- The members are accessed via the metadata connections: `python Copy code conn = urllib2.urlopen(group['metadata']['connections']['members']) members = json.loads(conn.read())['data']`

Conclusion

- This script effectively queries Facebook for groups related to a specific term, retrieves their details, and counts the members. Key steps include setting up the access token, making API requests, and handling potential issues with result availability.

Counting Members in Facebook Groups

1. Closing the Connection :

- After retrieving member data, the connection to the data source is closed: `python Copy code conn.close()`

2. Outputting Results :

- The script prints the group name and the number of members: `python Copy code print group['name'], len (members)`

3. Sample Results :

- Example results for the query on "programming" groups show that many groups have around **500 members** :
 - This is consistent with the **FQL documentation** , which states that queries to the `group_member` table are limited to **500 items** .

4. Limitations and Documentation :

- As of the current documentation, specific warnings about result limits in the **Graph API** are not well-

documented, unlike the FQL documentation.

- It's important to note that the results often represent a **random sample** of the total members due to this limit.

5. Sample Output :

- Sample results from the "programming" query demonstrate varying member counts:
 - For example:
 - **Graffiti Art Programming** : 492 members
 - **C++ Programming** : 495 members
 - **Basic Programming** : 495 members

6. Web Application Example :

- A sample web application that integrates much of the code from this chapter is available on **Google App Engine (GAE)**.
- Figure 9-4 showcases the results of the "programming" groups query.
- Users can customize the GAE-powered Facebook app or run local scripts for development.

7. Development Strategy :

- It's recommended to develop using local scripts for faster iteration and then integrate the functionality into the GAE codebase once stable.

Summary

The script effectively counts and displays the number of members in Facebook groups related to programming. It highlights the limitation of querying member data, where results may only represent a sample of the actual member count. This understanding is crucial when working with Facebook's APIs to manage data retrieval effectively.

Exploring Facebook Data with FQL

1. Sample Query Results :

- **Figure 9-4** displays results from querying "programming" groups. Users can click on links to explore deeper into the graph.

2. Using FQL for Advanced Queries :

- While the **Graph API** is straightforward for simple data retrieval, **Facebook Query Language (FQL)** is more suitable for complex queries and specific workflows.
- **FQL** allows you to perform sophisticated data manipulations beyond basic object interactions.

3. Documentation :

- Comprehensive **FQL documentation** is available online, providing detailed guidelines and examples.
- It's advisable to refer to this documentation for authoritative information instead of relying solely on brief explanations.

Summary

FQL enhances the ability to query and manipulate data within Facebook's ecosystem, particularly when dealing with more intricate data relationships. Utilizing both the Graph API and FQL effectively can optimize data handling and analysis.

Understanding Facebook Query Language (FQL)

1. FQL Basics :

- **FQL** mimics **SQL** syntax and allows for structured data queries on Facebook.
- **Query Structure** : FQL queries follow this format:
 - `select [fields] from [table] where [conditions]`
- Restrictions apply, such as:
 - Only **one table** name can be used in the `FROM` clause.
 - The `WHERE` clause is limited to indexed fields specified in the **FQL documentation** .

2. Executing FQL Queries :

- To run FQL queries, send them to one of the following API endpoints:
 - `https://api.facebook.com/method/fql.query`
 - `https://api.facebook.com/method/fql.multiquery`

3. Example Query :

- **Example 9-7** demonstrates a nested FQL query to fetch the names, genders, and relationship statuses of the logged-in user's friends: `sql Copy code select name, sex, relationship status from user where uid in (select target id from connection where source id = me() and target type = 'user')`
- **Explanation** :
 - The **subquery** retrieves user IDs of friends: `sql Copy code select target id from connection where source id = me() and target type = 'user'`
 - The `me()` directive represents the currently logged-in user.

4. Sample Results :

- The general format of results from the FQL query is shown in **Example 9-8** : `json Copy code [{ "name" : "Matthew Russell" , "relationship status" : "Married" , "sex" : "male" } , ...]`

5. Multiquery in FQL :

- An **FQL multiquery** allows running multiple queries at once, referencing results by name using the **hash symbol** .
- This provides more complex data retrieval in a single request.

Summary

FQL is a powerful tool for querying data on Facebook, providing a SQL-like experience with specific limitations. Understanding its structure and how to execute queries effectively can enhance data analysis capabilities on the platform.

FQL Multiquery Overview

1. FQL Multiquery Structure :

- An **FQL multiquery** allows you to combine multiple queries into a single request.
- Example 9-9 illustrates a multiquery that retrieves user and connection data: **json Copy code**

```
{ "name
sex_relationships    " : "select name, sex, relationship    status    from user \ where uid in
(select target    id    from #ids)" , "ids" : "select target    id    from connection where source
id    = me() \ and target    type    = 'user'" }
```

2. Results of Multiquery :

- Unlike single queries, both components of the multiquery return results. Example 9-10 shows how these results are structured: **json Copy code**

```
[ { "fql    result_set    " : [ { "target    id    " : -1 } , ...
] , "name" : "ids" } , { "fql    result_set    " : [ { "name" : "Matthew Russell" , "relationship
status    " : "Married" , "sex" : "male" } , ... ] , "name" : "name    sex_relationships    " } ]
```

3. Programmatic Execution :

- The query logic can be easily implemented in a small class.
- Example 9-11 demonstrates how to run FQL queries via a command line:
 - **Example Command 1: bash Copy code**

```
python facebook    _fql_query    .py 'select name, sex,
relationship    status    from user where uid in (select target    id    from connection where
source    id    = me())'
```
 - **Example Command 2: bash Copy code**

```
python facebook    _fql_query    .py '{"name
sex_relationships    " : "select name, sex, relationship    status    from user where uid in
(select target    id    from #ids)", "ids" : "select target    id    from connection where
source    id    = me()}"'
```

Summary

FQL multiqueries enhance data retrieval capabilities by allowing multiple queries in one request, returning structured results. This flexibility can be harnessed programmatically, making it easier to execute complex data analyses on Facebook.

FQL Query Class in Python

Overview : This example illustrates a small Python class designed to facilitate FQL (Facebook Query Language)

1. Class Definition :

- **Class Name** : FQL
- **Purpose** : Simplifies sending FQL queries to Facebook's API.

2. Key Components :

- **Endpoint** : The base URL for Facebook API methods is defined as: python Copy code `ENDPOINT = 'https://api.facebook.com/method/'`

3. Initialization :

- The constructor (`__init__`) accepts an **access token** to authenticate requests: python Copy code `def __init__(self, access_token = None): self.access_token = access_token`

4. Fetch Method :

- A private method `_fetch` is defined to handle API requests: python Copy code `def _fetch(cls, url, params=None): conn = urllib2.urlopen(url, data=urlencode(params)) try : return json.loads(conn.read()) finally : conn.close()`

5. Query Method :

- The `query` method processes standard FQL queries:
 - If the query starts with `{`, it calls `multiquery` for complex queries.
 - Otherwise, it formats the query for a single request:
- python Copy code `def query(self, q): if q.strip().startswith('{'): return self.multiquery(q) else : params = dict (query=q, access_token =self.access_token , format = 'json') url = self.ENDPOINT + 'fql.query' return self._fetch (url, params=params)`

6. Multiquery Method :

- The `multiquery` method handles multiple queries in one request: python Copy code `def multiquery(self, q): params = dict (queries=q, access_token =self.access_token , format = 'json') url = self.ENDPOINT + 'fql.multiquery' return self._fetch (url, params=params)`

7. Sample Usage :

- The script includes a way to run FQL queries from the command line: python Copy code `if __name__ == '__main__': try : ACCESS_TOKEN = open ('out/facebook.access_token').read() Q = sys.argv[1] except IOError: ...`

Summary

The FQL class encapsulates functionality for executing FQL queries on Facebook's API, making it easier to fetch data with minimal code. The class can handle both single and multiqueries, streamlining the process of interacting with Facebook's data.

Purpose : This Python snippet enables users to run FQL queries against Facebook's API, providing a simple interface for accessing user data.

1. Argument Handling :

- The script attempts to read the **access token** and **query** from command-line arguments: python Copy code `Q = sys.argv[2]`
- If the arguments are missing, it prompts an error message and logs in to obtain the access token: python Copy code `except IndexError: print >> sys.stderr, "Could not either find access token in 'facebook.access token ' or parse args." ACCESS TOKEN = login() Q = sys.argv[1]`

2. Query Execution :

- An instance of the `FQL` class is created with the access token: python Copy code `fql = FQL(access token =ACCESS TOKEN)`
- The FQL query is executed, and the results are printed in a formatted JSON output: python Copy code `result = fql.query(Q) print json.dumps(result, indent= 4)`

3. Sample Application :

- A sample Google App Engine (GAE) app included in the chapter allows users to run both FQL and Graph API queries, acting as a **playground** for experimentation.

Visualizing Facebook Data

Introduction : This section discusses how to analyze and visualize data from Facebook, equipping you with the tools needed for various projects.

1. Use Cases :

- Examples of visualizations include:
 - **Mutual Friendships** : Analyzing and visualizing all mutual friendships in your network.
 - **Group Friendships** : Focusing on mutual friendships within specific groups or based on criteria like gender.
 - **Data-Driven Game** : Creating a game that challenges users to identify friends based on their current location and hometowns.

2. Tools and Frameworks :

- The section emphasizes using the **JavaScript InfoVis Toolkit (JIT)** for creating interactive visualizations. JIT provides templates that can be easily customized for different data sets.

Summary

This content serves as a guide to executing FQL queries and visualizing Facebook data, highlighting potential projects and tools to enhance user interaction and analysis. With the foundational code in place, users can explore a wide range of data visualization opportunities.

Visualizing with RGraphs

Definition : An RGraph is a type of network visualization that arranges nodes in concentric circles starting from the center. This layout helps in understanding the relationships between nodes more intuitively.

1. Toolkits :

- RGraphs can be found in various visualization toolkits, notably the **JavaScript InfoVis Toolkit (JIT)** , which provides numerous examples to explore.

2. Comparison with Protovis :

- The **Node-Link tree** in Protovis is similar to the RGraph. However, JIT offers more **interactive examples** that can be easier for beginners to use and implement.

3. Data Preparation :

- A significant part of visualizing Facebook data involves **munging** (transforming) the raw data into a suitable format for visualization.
- RGraphs require a **predictable JSON structure** that contains a list of objects, where each object represents a node and its connections (adjacencies).

4. Example JSON Structure :

- Each node has:
 - **id** : A unique identifier.
 - **name** : The label for the node (e.g., "Matthew").
 - **adjacencies** : An array of connected node IDs.
 - **data** : Additional attributes, like:
 - **connections** : A string with labels of connected nodes (e.g., "Mark, Luke, John").
 - **normalized popularity** : A score indicating the node's popularity.
 - **sex** : Demographic information about the node.

Sample JSON :

```
json Copy code [ { "adjacencies" : [ "2" , "3" , "4" ] , "data" : { "connections" : "Mark  
Luke  
John" , "normalized popularity" : 0.0079575596817 , "sex" : "male" } , "id" : "1" , "name" :  
"Matthew" } , ... ]
```

Summary

RGraphs are effective for visualizing network data by organizing nodes in a radial layout. They require specific JSON formatting for optimal display. Tools like JIT provide interactive options, enhancing the ease of visualization compared to alternatives like Protovis. Understanding the data structure is crucial for effective visualization.

Objective : To calculate and visualize mutual friendships within your network of friends using an RGraph . This analysis helps identify popular individuals in your network as well as those who may not be as well-connected.

Steps to Gather Data

1. Get Friend IDs :

- Use an FQL query to retrieve the IDs of your friends.
- **Query** : sql Copy code `q = "select target_id from connection where source_id = me() and target_type = 'user'"` my_friends = [str(t['target_id ']) for t in fql.query(q)]

2. Calculate Mutual Friendships :

- Run a query to find pairs of friends who are mutual connections.
- **Query** : sql Copy code `q = "select uid1, uid2 from friend where uid1 in (%s) and uid2 in (%s)" % (",".join(my_friends), ",".join(my_friends))` mutual_friendships = fql(q)

3. Grab Additional Details :

- Fetch more information about each friend, like names and genders, to enhance the graph's presentation.
- **Query** : sql Copy code `q = "select uid, first_name, last_name, sex from user where uid in (%s)" % (",".join(my_friends),)` names = {unicode(u["uid"]): u["first_name"] + " " + u["last_name"][0] + "." for u in fql(q)}

Important Considerations

• Data Truncation :

- You may encounter **arbitrarily truncated results** when querying mutual friendships if you pass a large number of IDs. This is due to the computational complexity of comparing each friend with every other friend (an $O(n^2)$ operation).
- Instead of an error message, you might receive incomplete data, which can be surprising.

• Batch Processing :

- To address the truncation issue, break down the queries into smaller batches.
- **Example Code** : python Copy code `mutual_friendships = [] N = 50 # Batch size for i in range(len(my_friends) // N + 1): q = "select uid1, uid2 from friend where uid1 in (%s) and uid2 in (%s)" % (",".join(my_friends[i*N:(i+1)*N]), ",".join(my_friends[i*N:(i+1)*N])) mutual_friendships += fql(query=q)`

Summary

By following these steps, you can compute mutual friendships in your Facebook network and visualize the data as an RGraph. Be mindful of data truncation issues and employ batch processing to ensure you gather all relevant information. This process provides valuable insights into the connections within your social network.

Harvesting and Munging Friends Data for RGraph Visualization

This section outlines how to efficiently gather and prepare data from your Facebook friends for visualization using RGraph . The process is straightforward but requires attention to detail to avoid common pitfalls.

Overview of the Process

1. Setup and Access Token :

- The script begins by importing necessary libraries and defining paths for output and HTML templates.
- It attempts to read the **access token** from a file. If that fails, it checks for a command-line argument or prompts for login.

2. FQL Query to Get Friend IDs :

- The first FQL query retrieves the IDs of your friends: sql Copy code `q = 'select target_id from connection where source_id = me() and target_type = \' user \' my_friends = [str(t[\'target_id\']) for t in fql.query(q)]`

3. Calculate Mutual Friendships :

- To find mutual friendships, the script acknowledges that the Facebook API can return **arbitrarily truncated results** if too many IDs are passed at once.
- To mitigate this, it processes the friends in smaller batches: python Copy code `mutual_friendships = []
N = 50 # Batch size`

Important Considerations

• Truncated Results :

- Be aware that when querying a large number of friends, the API may truncate results. This is due to the computational load of processing large datasets in a single request.

• Batch Processing :

- The solution involves splitting friend queries into smaller batches to collect complete data: python Copy code `for i in range (len (my_friends) // N + 1): # Perform queries for mutual friendships
...`

• Multiple API Calls :

- Note that this method may lead to multiple API calls, which can result in large amounts of data being returned. Be prepared to handle and process this data efficiently.

Example Code

Here's an example of how the overall code is structured (simplified for clarity):

python Copy code

```
# Import necessary modules from facebook
_fql_query import FQL from facebook
_login import login # Set up
access token try : ACCESS_TOKEN = open ('out/facebook.access_token ').read() except IOError: ACCESS_TOKEN = sys.argv[ 1 ] if len (sys.argv) > 1 else login() fql = FQL(ACCESS_TOKEN ) # Query to get friend IDs my_friends = [ str (t[\'target_id\']) for t in fql.query( \'select target_id from connection where source_id = me() and target
```

```
type = 'user' ] ] # Query to calculate mutual friendships with batching mutual friendships = [] N = 50 # Batch size for i
in range ( len (my_friends ) // N + 1 ): # Execute query for mutual friendships ...
```

Conclusion

By following this approach, you can effectively gather and prepare data about mutual friendships in your Facebook network for visualization using RGraph . Pay attention to potential issues with data truncation and ensure that your queries are efficient to avoid overwhelming the API.

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Processing Mutual Friendships and Preparing Data for Visualization

This section explains how to process mutual friendships from your Facebook network and prepare the data for visualization, focusing on clarity and detail.

Looping Through Friends

1. Batch Processing for Mutual Friendships :

- The following loop iterates through your friends in batches to gather mutual friendship data: python Copy code

```
for i in range ( len (my_friends ) // N + 1 ): q = 'select uid1, uid2 from friend
where uid1 in (%s) and uid2 in (%s)' \ % ( ','.join(my_friends ), ','.join(my_friends
[i * N:(i + 1 ) * N])) mutual_friendships += fql.query(q)
```
- Here, N is the batch size, which helps manage the number of IDs processed in each query, preventing truncation issues.

Gathering Friend Details

1. Fetching Friend Information :

- A query is made to retrieve details such as **first name** , **last name** , and **sex** for each friend: python Copy code

```
q = 'select uid, first_name , last_name , sex from user where uid in (%s)' \ % (
','.join(my_friends ), ) results = fql.query(q)
```
- It's important to note that not every user ID will have associated information, so handling missing data is necessary.

2. Creating Name and Sex Dictionaries :

- Two dictionaries are constructed to map user IDs to their names and sexes: python Copy code

```
names = dict ([ (unicode(u[ 'uid' ]), u[ 'first_name ' ] + ' ' + u[ 'last_name ' ] [ 0 ] + '.' )
for u in results]) sexes = dict ([ (unicode(u[ 'uid' ]), u[ 'sex' ]) for u in results])
```

Consolidating Friendship Data

1. Building the Friendship Map :

- An empty dictionary `friendships` is initialized to hold connection information: python Copy code

```
friendships = {}
```
- The code iterates over `mutual_friendships` to populate this dictionary: python Copy code

```
for f in mutual_friendships : (uid1, uid2) = (unicode(f[ 'uid1' ]), unicode(f[ 'uid2' ])) # Retrieve names, handle missing data name1 = names.get(uid1, 'Unknown' ) name2 = names.get(uid2, 'Unknown' )
```
- It checks if each user ID is already present in the dictionary. If it is, it appends the new friend to their list; if not, it creates a new entry: python Copy code

```
if friendships.has_key (uid1): if uid2 not in friendships[uid1][ 'friends' ]: friendships[uid1][ 'friends' ].append(uid2) else : friendships[uid1] = { 'name' : name1, 'sex' : sexes.get(uid1, '' ), 'friends' : [uid2]}
```

Preparing Output for Visualization

1. Output for JavaScript InfoVis Toolkit (JIT) :

- The final step is to prepare the data for visualization: python Copy code

```
jit_output = [] for fid in friendships: friendship = friendships[fid] adjacencies = friendship[ 'friends' ] connections = ' '.join([names.get(a, 'Unknown' ) for a in adjacencies]) normalized_popularity = 1.0 * len (adjacencies) / len (friendships) sex = friendship[ 'sex' ]
```
- This block formats the adjacency data, calculating a **normalized popularity score** based on the number of connections relative to the total number of friendships.

Summary

This process effectively gathers and organizes data about mutual friendships, including handling potential missing information. The structured approach prepares the data for visualization, allowing for insights into social network dynamics and relationships.

Preparing and Exporting Visualization Data

This section details how to prepare the data for visualization and export it for use in an interactive format.

Structuring the JIT Output

1. Building the JIT Output Structure :

- Each friendship entry is added to the `jit_output` list, formatted as follows: python Copy code

```
jit_output.append( { 'id' : fid, 'name' : name1, 'sex' : sex, 'popularity' : normalized_popularity, 'friends' : adjacencies })
```

```
output.append({ 'id' : fid, 'name' : friendship[ 'name' ], 'data' : { 'connections' :
connections, 'normalized_popularity' : normalized_popularity , 'sex' : sex },
'adjacencies' : adjacencies, })
```

- This structure includes:

- **id** : Unique identifier for the friend.
- **name** : Name of the friend.
- **data** : Contains additional details like **connections** , **normalized popularity** , and **sex** .
- **adjacencies** : Lists the friend's direct connections.

File Management

1. Creating Output Directory :

- Check if the output directory exists, and create it if not: python Copy code `if not os.path.isdir('out') : os.mkdir('out')`

2. Copying Dependencies :

- Copy necessary files and directories for the visualization: python Copy code `shutil.rmtree('out/jit' , ignore_errors = True) shutil.copytree('../web_code /jit' , 'out/jit')`

Writing HTML and JSON Files

1. Generating the HTML File :

- Open the HTML template and write the JSON data into it: python Copy code `html = open (HTML_TEMPLATE).read() % (json.dumps(jit_output),) f = open (os.path.join(os.getcwd(), 'out' , 'jit' , 'rgraph' , OUT), 'w') f.write(html) f.close()`
- This produces an HTML file for use in a browser.

2. Exporting JSON Data :

- Write the `jit_output` data to a standard JSON file for future analysis: python Copy code `json_f = open (os.path.join('out' , 'facebook.friends.json'), 'w') json_f.write(json.dumps(jit_output , indent= 4)) json_f.close()`

Opening the Visualization

1. Launching in a Browser :

- The generated HTML file is opened in the user's default web browser: python Copy code `webbrowser.open('file://' + f.name)`

Considerations for Large Networks

- If you have a **large friend network** , consider filtering the friends visualized by meaningful criteria. This will help manage the data and improve clarity in the results. An example of filtering by group can be found in the provided materials.

Summary

This section outlines how to format and export data for an interactive visualization of your social network, including generating both HTML and JSON files. With proper setup, you can visualize connections, popularity, and other attributes within your friend network effectively.

Visualizing Facebook Data with RGraph and Sunburst

RGraph Visualization

- **RGraph** : A type of visualization that displays data in concentric circles, making it easy to visualize connections in a social network.
- **Example Use** : In Figure 9-5, you can see:
 - A **large RGraph** representing a network of over **500 friends** .
 - A **smaller RGraph** showing mutual friends within a specific group.

Sunburst Visualization

- **Sunburst Visualization** : A method for visualizing hierarchical data, resembling sunburst patterns.
- **Appearance** : It gets its name from its visual similarity to sunburst images, like the one on the **Imperial Japanese Army** flag, shown in Figure 9-6.
- **Features** :
 - **Hierarchical Structure** : Ideal for rendering tree-like data structures.
 - **Data Consumption** : Like RGraph, it uses a simple **graph-like JSON structure** .
 - **Event Handlers** : Provides built-in handlers for user interactions, making it interactive.
 - **Insightful Layout** : The layout helps users quickly grasp the relationships and hierarchies within the data.

Summary

Both RGraph and Sunburst visualizations are effective for displaying social network data, each offering unique perspectives. RGraphs are better for showing direct connections, while Sunbursts excel at representing hierarchical relationships and offering immediate visual insights.

Visualizing Social Networks with Sunburst

Sunburst Overview

- **Sunburst Visualization** : Represents hierarchical data in a circular layout, allowing easy interpretation of relative sizes and relationships within data.
- **Intermediate Nodes** : The size of each layer indicates the **degree of popularity** or presence of nodes (e.g., friends) based on area coverage.

Gender Segmentation

- The Sunburst can effectively show demographic data, such as **gender distribution** within a social network.
- **Example from Figure 9-6** : Illustrates that about **two-thirds** of the network members are female, visually adjacent to their respective sector.

Implementation Example

- **Example 9-14** : Demonstrates how to adapt data from an RGraph to create a Sunburst visualization segmented by gender.
 - **\$angularWidth Parameter** : A relative measure that helps scale the sectors based on the data.
 - **Popularity Scaling** : The area occupied by each friend reflects their popularity, providing an intuitive visual cue.
 - **Privacy Considerations** : Friends with privacy settings blocking gender information are ignored, leading to an empty string for gender.
 - **Tooltips** : Hovering over a section reveals mutual friends, enhancing interactivity and detail.

Code Snippet Overview

- **facebook_sunburst .py** :
 - **File Handling** : Reads previously stored JSON data containing friend information.
 - **Color Definitions** : Predefined colors for visual elements to enhance aesthetics.
 - **Primary Output** : Compiles the data structure for the Sunburst visualization.

Summary

Sunburst visualizations provide a powerful tool for analyzing social network data by illustrating hierarchical relationships and demographic distributions. They enable quick insights into the network's composition, such as gender ratios, while offering interactive features for deeper exploration of individual connections.

Simplified Notes on Code Structure and Functionality

Data Structure Overview

- **Data Object** : Represents users and their attributes.
 - Example: 'data': {'\$type': 'none'}, 'children': [],

Template for Friends

- **Template Definition** : python Copy code

```
template = { 'id' : 'friends' , 'name' : 'friends' , 'data' : { 'connections' : '' , '$angularWidth' : 1 , '$color' : '' }, 'children' : [], }
```

Gender-Based Friend Organization

- **Loop through Genders** : For each gender ('male', 'female'):
 - **Create Gender Object** :
 - Clone the template.
 - Update **ID** and **Name** to include gender.
 - Assign a **Color** based on gender index.

Finding Friends by Gender

- **Filter Friends** :
 - Use a list comprehension to find friends matching the current gender (`friends` `by_gender`).
- **Load Friends into Gender Object** :
 - For each friend:
 - Clone the template again.
 - Set **ID** and **Name** to the friend's information.
 - Assign a **Color** .
 - Set **Angular Width** based on the number of connections (popularity).
 - Store **Connections** for tooltip display.
 - Append the friend object to the gender object's **children** .

Output Structure

- **Appending Gender Objects** : Add the populated gender object to a higher-level structure (`jit` `output` `['children']`).

Output Directory Management

- **Check and Create Output Directory :**
 - Ensure the output directory exists or create it.
- **Copy Dependencies :**
 - Remove old dependencies and copy new ones from the specified path.

Key Concepts

- **Deepcopy :** Creates a new copy of objects to prevent mutation of original data.
- **Adjacencies :** Refers to the connections or relationships each friend has.
- **HTML TEMPLATE :** Points to web dependencies necessary for rendering the visual output.

Summary

This code organizes friends based on gender and visualizes connections using a template structure, efficiently managing data and directory outputs.

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Simplified Notes on HTML and Data Visualization

Writing HTML Output

- **Load HTML Template :**
python Copy code `html = open (HTML_TEMPLATE).read() % (json.dumps(jit_output),)`
 - This reads the HTML template and formats it using the JSON data (`jit_output`).
- **Save Output to File :**
python Copy code `f = open (os.path.join(os.getcwd(), 'out' , 'jit' , 'sunburst' , OUT), 'w')`
`f.write(html) f.close()`
 - Opens a file in the specified directory and writes the HTML content to it.
- **Print Confirmation :**
python Copy code `print 'Data file written to: %s' % f.name`
 - Outputs the file path where the data has been saved.
- **Open Web Page :**
python Copy code `webbrowser. open ('file://' + f.name)`

- Launches the saved HTML file in the default web browser.

Enhancing Data Visualization

- **Multiple Criteria Grouping :**
 - While the example groups friends by **gender** and **popularity** , you can expand this to include other criteria.
 - Example: Visualize by **gender** first, then **relationship status** to see correlations.

Visualizing with Spreadsheets

- **Old-Fashioned Method :**
 - Instead of complex visualizations, consider using a **spreadsheet** for data analysis.
 - Save the JSON output as a local file, which can be transformed into a **CSV** format.
- **Creating CSV for Analysis :**
 - Use the CSV to load into a spreadsheet program to analyze data distributions.
 - Example: Generate a **histogram** to show the popularity of friends in your network.

Key Concepts

- **HTML TEMPLATE** : A placeholder for your HTML structure.
- **JSON** : A format for representing structured data, ideal for data exchange.
- **CSV** : A simple file format for data storage, easy to open in spreadsheet applications.

Summary

This section details the process of writing HTML output from JSON data, enhancing visualizations with additional criteria, and suggests using spreadsheets for straightforward data analysis.

Simplified Notes on Sunburst Visualization

Overview of Sunburst Visualization

- **Definition** : A **Sunburst visualization** is a circular graphic that represents hierarchical data, resembling the sun's rays.
- **Inspiration** : Named for its similarity to sun symbols, such as the one on the **Japanese Imperial Army flag** .

Key Insights from Visualization

- **Gender Distribution** :
 - The visualization illustrates that approximately **2/3 of the friends network is female** .
 - About **1/3 is male** .

Importance of Visualization

- **Visual Representation** : Helps in easily understanding the composition of a social network.
- **Hierarchical Data** : Effectively displays relationships and proportions among different categories (in this case, gender).

Summary

The Sunburst visualization is a circular representation of hierarchical data, effectively showing that two-thirds of a friends network are female, while one-third are male.

Simplified Notes on Exporting Data for Spreadsheet Analysis

Script Overview

- **Purpose** : The script (`facebook_popularity_spreadsheet.py`) exports Facebook friends' data to a CSV format for easy analysis in a spreadsheet.

Key Components

- **Imports** :
 - Libraries: `os` , `sys` , `json` , `operator` .

- **Data Loading :**

python Copy code `DATA = open (sys.argv[1]).read() data = json.loads(DATA)`

- Loads data from a JSON file (output from a previous script).

- **Popularity Data Extraction :**

python Copy code `popularity_data = [(f['name'], len (f['adjacencies'])) for f in data]`
`popularity_data = sorted (popularity_data , key=operator.itemgetter(1))`

- Creates a list of tuples with **friend names** and their **connection counts** .
- Sorts the data by the number of connections.

- **CSV Formatting :**

python Copy code `csv_data = [] for d in popularity_data : csv_data .append('%s\t%s' % (d[0], d[1]))`

- Prepares data for CSV by formatting it as tab-separated values.

- **Output Directory :**

python Copy code `if not os.path.isdir('out'): os.mkdir('out')`

- Checks if the output directory exists; if not, it creates it.

- **File Writing :**

python Copy code `filename = os.path.join('out' , 'facebook.spreadsheet.csv') f = open (filename, 'w') f.write('\n' .join(csv_data)) f.close()`

- Saves the formatted data into a CSV file.

- **Confirmation :**

python Copy code `print 'Data file written to: %s' % filename`

- Outputs the file path of the saved CSV.

Data Visualization Insights

- **Histogram Analysis :** Visualizing data as a histogram reveals connection patterns.
 - **Distribution Characteristics :**
 - A perfectly connected network would show a flat distribution.
 - In the provided example, the second most popular individual has about half the connections of the most popular.
- **Connection Distribution :**
 - Follows a **Zipf-like distribution** with a long tail, closely fitting a **logarithmic trendline** .
- **Social Network Dynamics :**
 - **Logarithmic Distribution :** Common in large, diverse networks, where few individuals have many connections while most have relatively few.
 - Aligns with the **Pareto Principle** (80-20 rule): “20% of the people have 80% of the friends.”

Summary

This script exports Facebook friends' data to a CSV file for analysis, providing insights into the social network's connectivity patterns, which often follow a logarithmic distribution, illustrating that a small number of individuals hold the majority of connections.

Simplified Notes on Visualizing Mutual Friendships Within Groups

Overview of Mutual Friendships Visualization

- **Purpose** : To visualize mutual friendships in a social network, using a graph format.
- **Implementation** : Example 9-13 shows how to achieve this with a **canvas element** in modern browsers, which can handle large graphs effectively.

User Interaction Features

- **Click Handler** :
 - When a node (friend) is clicked, it displays:
 - The **connections** of that friend.
 - A **normalized popularity score** : calculated as the number of connections divided by the total connections in the network.

Filtering Friendships

- **Need for Filtering** : While viewing the entire network is informative, focusing on smaller groups can be more insightful.
- **Group-Based Filtering** :
 - Example 9-16 demonstrates how to filter the JSON output based on a specified **group criterion** .
 - This method retains complete **connections data** for the entire network, allowing analysis of a friend's broader relationships even if those friends aren't part of the selected group.

Potential Analyses

- **Group Analysis Opportunities** :
 - Compare connections between **male** and **female friends** .
 - Conduct **clique analysis** to identify closely connected groups.
 - Explore various other analyses based on group membership.

Visualization Example

- **Figure 9-7** : Illustrates the distribution of popularity within a Facebook friends network, highlighting a **logarithmic trendline** .

Summary

The implementation visualizes mutual friendships in a social network, incorporating user interaction features. It allows for filtering by group criteria, retaining valuable connections data for further analysis, with numerous possibilities for in-depth friendship dynamics exploration.

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Simplified Notes on Harvesting and Munging Data to Visualize Mutual Friends by Group

Script Overview

- **Purpose :** The script (`facebook _filter_rgraph_output_by_group .py`) filters and visualizes mutual friends within a specified Facebook group.

Key Components

- **Imports :**
 - Libraries: `os , sys , json , facebook , webbrowser , shutil .`
- **HTML Template :**
 - Set the path for the HTML template:
python Copy code `HTML_TEMPLATE = '../web_code /jit/rgraph/rgraph.html'`
- **Data Loading :**
python Copy code `DATA = sys.argv[1] rgraph = json.loads(open (DATA).read())`
 - Loads JSON data from a file generated by a previous script.

Access Token Management

- **Access Token Retrieval :** python Copy code `try : ACCESS_TOKEN = open ('out/facebook.access_token').read()`
 - Attempts to read the access token from a file.
- **Fallback Method :**
 - If the token is not found, it checks command-line arguments or prompts the user to log in:
python Copy code `ACCESS_TOKEN = login()`

Graph API Interaction

- **Initialize Graph API :**

```
python Copy code gapi = facebook.GraphAPI(ACCESS_TOKEN)
```

- **Fetch Groups :**

```
python Copy code groups = gapi.get_connections('me', 'groups')
```

- Retrieves the user's Facebook groups.

User Group Selection

- **Display Groups :** python Copy code

```
for i in range ( len (groups[ 'data' ])): print '%s' % (i, groups[ 'data' ][i][ 'name' ])
```

 - Lists available groups for user selection.
- **Group Choice :** python Copy code

```
choice = int (raw_input ( 'Pick a group, any group: ' )) gid = groups[ 'data' ][choice][ 'id' ]
```

 - Prompts the user to select a group by its index.

Next Steps in Data Processing

- **Find Friends in the Group :**
 - The next step involves querying friends in the selected group using **FQL** (Facebook Query Language).

Summary

This script filters mutual friendships based on a selected Facebook group. It manages access tokens, interacts with the Facebook Graph API to retrieve user groups, and allows the user to select a group for further analysis.

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Simplified Notes on Querying and Visualizing Group Friendships

Query to Fetch Group Members

- **FQL Query :** sql Copy code

```
select uid from group_member where gid = %s and uid in ( select target_id from connection where source_id = me() and target_type = 'user' )
```

 - This query retrieves user IDs (**uids**) of friends who are members of a specified group (**gid**).

Filtering Friends

- **Get User IDs :**

python Copy code `uids = [u['uid'] for u in fql.query(q)]`

- Collects user IDs from the query results.

- **Filter Graph Data :**

python Copy code `filtered_rgraph = [n for n in rgraph if n['id'] in uids]`

- Filters the original graph data (`rgraph`) to include only nodes (friends) that are in the selected group.

Trimming Adjacency Lists

- **Update Connections :** python Copy code `for n in filtered_rgraph : n['adjacencies'] = [a for a in n['adjacencies'] if a in uids]`
 - For each friend in the filtered graph, it trims their adjacency list to include only those friends also in the selected group.

Output Directory Management

- **Create Output Directory :**

python Copy code `if not os.path.isdir('out'): os.mkdir('out')`

- Checks for the existence of the output directory; creates it if missing.

- **Copy HTML Dependencies :**

python Copy code `shutil.rmtree('out/jit' , ignore_errors = True)`
`shutil.copytree('../webcode /jit' , 'out/jit')`

Generating HTML Output

- **Read and Write HTML :**

python Copy code `html = open (HTML_TEMPLATE).read() % (json.dumps(filtered_rgraph),)`
`f = open (os.path.join(os.getcwd(), 'out' , 'jit' , 'rgraph' , OUT), 'w')`
`f.write(html)`
`f.close()`

- Loads the HTML template, inserts the filtered graph data, and saves the output file.

- **Confirmation and Browser Open :**

python Copy code `print 'Data file written to: %s' % f.name`
`webbrowser.open ('file://' + f.name)`

- Outputs the file path and opens the generated HTML file in a web browser.

Further Analysis Opportunities

- **Group Comparisons :**

- You can compare connectedness among different groups and identify friends involved in multiple groups.

Image Export Option

- **Canvas to Image :** javascript Copy code `//grab the canvas element`
`var canvas = document .`

```
getElementById ( "infovis-canvas" ); //now prompt a file download window . location = canvas.  
toDataURL ( "image/png" );
```

- This JavaScript snippet allows users to download the visualized graph as a PNG image.

Summary

The script filters mutual friendships within a Facebook group, updates connection data, generates HTML output for visualization, and provides options for further analysis and image export.

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Simplified Notes on "Where Have My Friends All Gone?" Data-Driven Game

Overview of the Game

- **Objective** : A fun game to test your knowledge of friends by comparing their **hometowns** and **current locations** .
- **Data Utilization** : The game uses data from Facebook, processed through **FQL queries** .

Key Components

- **Tree Widget** :
 - The game incorporates a **tree widget** for visual representation, similar to one used in previous sections.
- **Data Transformation** :
 - The focus is on transforming the data retrieved from FQL queries into a suitable format for the tree widget.

FQL Query

- **Query Structure** : sql Copy code `q = ""select name, current_location , hometown_location from user where uid in (select target_id from connection where source_id = me())""`
 - This query retrieves **names** , **current locations** , and **hometowns** of friends based on their user IDs.

Output Format

- **Target JSON Structure** :
 - The final JSON format must be compatible with the Dojo tree widget:
- ```
json Copy code { "items" : [{ "name" : "Alabama (2)" , "children" : [{ "state" : "Alabama" ,
"children" : [{ "state" : "Tennessee" , "name" : "Nashville, Tennessee (1)" , "children" : [{
```

```
"name" : "Joe B." }] }] , "name" : "Prattville, Alabama (1)" , "num from_hometown " : 1 }] }
, { "name" : "Alberta (1)" }] }
```

- This structure organizes friends by state and city, indicating the number of friends from each location.

## Examples and Resources

- **Example Codes :**
  - Example 9-17 shows the required JSON format.
  - Example 9-18 provides Python code for generating the desired output.
- **Source Code Availability :**
  - The complete source code for this implementation is available online at [GitHub](#).

## Summary

This section introduces a data-driven game that analyzes friends' hometowns and current locations using Facebook data. It emphasizes the use of FQL queries to gather necessary information and the transformation of that data into a JSON format suitable for a tree widget display.

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## Notes on Visualizing Friends' Locations and Hometowns

### Data Structure Example

- **JSON Structure :** json Copy code "children" : [ { "state" : "Alberta" , "children" : [ { "state" : "Alberta" , "name" : "Edmonton, Alberta (1)" , "children" : [ { "name" : "Gina F." } ] } ] , "name" : "Edmonton, Alberta (1)" , "num from\_hometown " : 1 } ] , "label" : "name"
  - This structure represents friends grouped by **state** and **city** , showing names and counts.

### Hierarchical Display

- **Final Widget :**
  - Displays friends by current location and hometown (e.g., Jess C. lives in Tuscaloosa, AL, but is from Princeton, WV).
  - Provides insight into migration patterns and local distributions of friends.

### Data Collection

- **FQL Query :**
  - A simple query retrieves essential data about friends' locations and hometowns.

## Visualization Process

- **Tree Widget Usage :**
  - Similar to previous examples, the same source code is used for visualization.
  - Data must be formatted and captured to be compatible with the tree widget.

## Potential Enhancements

- **Integration Ideas :**
  - **Google Maps** : Link to map locations for unfamiliar areas.
  - **Additional Variables** : Include age, gender, college, or professional affiliations for deeper analysis.
  - **KML Emission** : Generate KML files for visualization in **Google Earth** to analyze geographically.

## Summary

This section discusses visualizing friends based on their current locations and hometowns using a hierarchical tree widget. It emphasizes the simple data collection process via FQL queries and suggests enhancements for a richer user experience.

## Notes on "Where Are They Now?" Game and Data Harvesting

### Game Overview

- **Title :** "Where Are They Now?"
  - A fun and informative game that tests knowledge of friends' current locations and hometowns.

### Example Code for Data Collection

- **Script :** facebook \_get\_friends\_current\_locations\_and\_hometowns .PY

## Code Structure :

### 1. Import Libraries :

- Uses `sys` , `json` , and `facebook` libraries, along with custom modules for FQL queries and Facebook login.

### 2. Access Token Handling :

- Tries to read the **access token** from a file: `python Copy code try : ACCESS_TOKEN = open ( "facebook.access_token" ).read()`
- If the file is not found, it attempts to read it from command-line arguments: `python Copy code ACCESS_TOKEN = sys.argv[ 1 ]`
- If both methods fail, it prompts the user to log in: `python Copy code print >> sys.stderr, "Could not either find access token or parse args. Logging in..." ACCESS_TOKEN = login()`

## Summary

This section outlines the "Where Are They Now?" game, which engages users in identifying friends' current locations and hometowns. The provided code demonstrates how to collect necessary data from Facebook using access tokens, either from a file or command-line input, while also handling potential errors effectively.

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## Notes on Processing FQL Query Results for Hierarchical JSON Output

### FQL Query Execution

- **Purpose** : Create a JSON output suitable for a hierarchical tree widget.
- **Query** : `sql Copy code select name, current_location , hometown_location from user where uid in ( select target_id from connection where source_id = me() and target_type = 'user' )`
- **Library Used** : FQL (Facebook Query Language) with an **access token** for authentication.

## Data Processing

### 1. Initialize Data Structure :

- Use a dictionary ( `current_by_hometown` ) to group friends by **hometown** and their **current location** .

### 2. Iterate Through Results :

- For each result, extract the **current location** and **hometown** :
  - If either is missing, assign "Unknown".
  - Format the locations as "City, State".

### 3. Building the Dictionary :

- Check if the hometown already exists in the dictionary:
  - If it does, check for the current location.
  - Append the friend's name to the corresponding list.
  - If it doesn't exist, create a new entry for that hometown and current location.

## Creating Hierarchical Structure

#### • Prepare Items for Tree Display :

- For each hometown in `current` by `hometown` :
  - Calculate the total number of friends from that hometown.
  - Format the name as "Hometown (Number of Friends)".
- Extract the state from the hometown for potential further use.

## Summary

This process involves querying Facebook data to gather friends' current locations and hometowns. It organizes this data into a hierarchical structure using a dictionary, which makes it easy to visualize as a tree widget. The approach allows for flexible data manipulation and analysis based on friends' geographic information.

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## Notes on Creating Hierarchical JSON Structure for Friends' Locations

### Building JSON Items

#### 1. Create Base Item :

- Each item represents a **hometown** : python Copy code 

```
item = { 'name' : name, 'state' : hometown
state , 'num from_hometown ' : num from_hometown} item['children'] = []
```

#### 2. Populate Children :

- For each **current location** associated with the hometown:
  - Extract the **state** from the current location.
  - Append to `item['children']` :
    - Format as "Current Location (Number of Friends)".
    - Include a list of friends from that location, abbreviated to their first names.

#### 3. Sort Children :

- Sort `item['children']` alphabetically by **state** .

## Grouping by State

### 1. Sort Outer Items :

- Sort the main `items` list by **state** .

### 2. Group Items by State :

- Initialize lists for all `items_by_state` and grouped `items` .
- Iterate through `items` :
  - If the **state** matches the current state, accumulate counts and group items.
  - If it changes, save the previous state's group and reset for the new state.

### 3. Final Grouping :

- Append the last group to all `items_by_state` .

## Output Generation

- Emit the final JSON structure, suitable for a hierarchical tree widget: python Copy code 

```
print json.dumps({
'items' : all items_by_state , 'label' : 'name' }, indent= 4)
```

## Summary

This process involves constructing a hierarchical JSON output that organizes friends based on their hometown and current location . The data is grouped and sorted to enhance readability and usability in a tree widget format, allowing for better visualization of friends' locations.

## Visualizing Wall Data as a (Rotating) Tag Cloud

### Overview

Analyzing the language used on your Facebook wall or in your news feed can provide valuable insights. A tag cloud is a visual representation of text data, showing the frequency of terms. Instead of using a basic tag cloud, we can create a customizable and interactive version using the open-source tool WP-Cumulus .

### Key Steps to Create a Tag Cloud

### 1. Input Data Preparation :

- Generate a **frequency distribution** of terms from the data collected.
- Structure the data as a list of **[term, URL, frequency]** tuples.
- While URLs can be left empty initially, you can enhance the logic later to link terms back to their source posts.

### 2. Fetch Data :

- Use the **Graph API** to retrieve multiple pages of news feed data from your Facebook wall.

### 3. HTML Template :

- Integrate the prepared data into an HTML template with the necessary boilerplate. This template will display the tag cloud.

#### Example Code Snippet : facebook \_tag\_cloud .py

python Copy code

```
import os import sys import urllib2 import json import webbrowser import nltk from cgi import escape from facebook
_login import login # Access token handling try : ACCESS_TOKEN = open ('out/facebook.access_token ').read()
except IOError: try : ACCESS_TOKEN = sys.argv[1] except IndexError: ACCESS_TOKEN = login()
```

#### Additional Features

- With more work, you can create a mapping of which terms appear in which posts, allowing the tag cloud terms to link back to the original content.
- For implementation details and templates, visit the provided GitHub link.

#### Summary

This approach allows for an engaging and informative way to visualize unstructured data from your Facebook interactions using an interactive WP-Cumulus tag cloud, enhancing the user experience with customizable features.

## Creating a Rotating Tag Cloud from Facebook Data

### Overview

This section details how to create a tag cloud using data from your Facebook wall. The tag cloud visually represents the frequency of terms found in your posts, utilizing the WP-Cumulus tool for an interactive display.



### 1. Access Token Handling :

- If the local **access token** isn't found, the user is prompted to log in:

```
python Copy code print >> sys.stderr, "Could not find local access token or parse args. Logging in..." ACCESS_TOKEN = login()
```

### 2. API Setup :

- **Base URL** for fetching posts from your Facebook wall:

```
python Copy code BASE_URL = 'https://graph.facebook.com/me/home?access_token ='
```

### 3. HTML Template and Output :

- Location for the HTML template and output file:

```
python Copy code HTML_TEMPLATE = '../web_code/wp_cumulus/tagcloud_template.html' OUT_FILE = 'out/facebook.tag_cloud.html'
```

### 4. Pagination and Data Fetching :

- Define the number of pages to fetch and initialize variables:

```
python Copy code NUM_PAGES = 5 messages = [] current_page = 0 url = BASE_URL + ACCESS_TOKEN
```

- Loop through pages to collect messages:

```
python Copy code while current_page < NUM_PAGES : data = json.loads(urllib2.urlopen(url).read()) messages += [d['message'] for d in data['data'] if d.get('message')] current_page += 1 url = data['paging']['next']
```

### 5. Frequency Distribution :

- Use **NLTK** to compute the frequency of terms across the collected messages:

```
python Copy code fdist = nltk.FreqDist([term for m in messages for term in m.split()])
```

### 6. Stop Words :

- Customize a list of **stop words** (common words to exclude):

```
python Copy code stop_words = nltk.corpus.stopwords.words('english') stop_words += ['&' , '.', '?', '!']
```

### 7. Output Preparation :

- Filter and sort terms based on their frequency:

```
python Copy code raw_output = sorted ([escape(term), ' ', freq] for (term, freq) in fdist.items() if freq > MIN_FREQUENCY and term not in stop_words], key= lambda x: x[2])
```

### 8. Font Size Scaling :

- Calculate font size based on term frequency to create a visually appealing cloud:

```
python Copy code def weightTermByFreq (f): return (f - min_freq) * (MAX_FONT_SIZE - MIN_FONT_SIZE) / (max_freq - min_freq) + MIN_FONT_SIZE
```

### 9. Generate HTML Page :

- Substitute the weighted term data into the HTML template:

```
python Copy code html_page = open (HTML_TEMPLATE).read() % (json.dumps(weighted_output),)
```

## Conclusion

By following these steps, you can create a dynamic and interactive tag cloud that visually represents the most common terms from your Facebook posts, providing insight into your social media interactions.

## Saving and Displaying the Tag Cloud

### 1. Saving the HTML Output :

- Open the output file and write the generated HTML for the tag cloud:

python Copy code `f = open (OUT_FILE , 'w' ) f.write(html_page ) f.close()`

- Confirm the output file's path:

python Copy code `print 'Data file written to: %s' % f.name`

### 2. Opening in Browser :

- Launch the tag cloud in a web browser:

python Copy code `webbrowser.open ( 'file://' + os.path.join(os.getcwd(), OUT_FILE ))`

### 3. Sample Results :

- The tag cloud created during a Boise State versus Virginia Tech football game showed that "I" was the most common word in the feeds. This indicates the simplicity of generating visualizations from social media data.

## Extending Functionality

- **Advanced Techniques** : For more meaningful tag clouds, consider using **Natural Language Processing (NLP)** and filtering techniques to focus on significant terms rather than just frequency.
- **Entity Recognition** : Instead of simple tokenization, apply advanced analytics to identify entities of interest, as discussed in Chapter 8.

## Closing Remarks

- **Vast Opportunities** : Facebook's APIs allow for extensive data exploration and application development. This chapter introduces tools to start building data-driven applications, but many possibilities remain.
- **Further Exploration** :
  - Visualize text from friends' walls using an entity-centric approach.
  - Analyze structured data from the Graph API to identify active users based on status updates and comments.
  - Cluster friends based on their "Likes" and analyze these preferences with pivot tables or graphs.

These steps encourage creativity in utilizing social media data for insightful analysis and applications.

- **Definition** : A **rotating tag cloud** is a visual representation of text data, where the size of each term indicates its frequency or importance. This format makes it easy to see which topics or terms are most prevalent in the data.
- **Customization** : These tag clouds are **highly customizable** , allowing users to adjust visual elements such as colors, fonts, and layouts. This flexibility enhances user engagement and interaction.
- **Ease of Setup** : Creating a rotating tag cloud requires minimal effort. By utilizing simple scripts and templates, users can quickly generate and display the cloud based on their data.
- **Applications** : This visualization can be applied to various data sources, particularly social media feeds, to analyze language and themes within posts.
- **Visual Appeal** : The dynamic nature of a rotating tag cloud attracts attention, making it an effective tool for presenting data in an engaging way.

Overall, a rotating tag cloud is a powerful and visually appealing way to summarize and analyze textual data with little technical effort.

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## Chapter 10: The Semantic Web Overview

- **Purpose** : This chapter serves as a **brief discussion** on the **semantic web** , building on previous content about the social web and its data applications. It aims to inspire excitement about future possibilities rather than provide exhaustive details.
- **Definition of Semantic Web** :
  - The **semantic web** refers to a framework for sharing information that emphasizes **meaning** .
  - **Semantics** can be defined as providing "enough meaning to result in an action." This means the semantic web focuses on structuring data so it can be easily interpreted and used, not just by humans but also by machines.
- **Machine Understanding** :
  - A key aspect of the semantic web is its ability to enable machines to **understand** shared information. This involves creating data formats that are clear and unambiguous, allowing automated systems (like web robots) to extract and utilize this information effectively.
- **Current Developments** :
  - The chapter references **microformats** from Chapter 2 as an example of early steps towards machine-readable data.
  - It also mentions **Facebook's Open Graph** from Chapter 9, which integrates a structured graph model into the web, further facilitating machine understanding.
- **Future Possibilities** :
  - The discussion encourages exploration of how the semantic web could revolutionize information sharing and decision-making by enabling better communication between data sources and automated systems.

In summary, this chapter presents an overview of the semantic web's goals and implications, focusing on how enhanced

## The Evolution of the Web

- **Internet Overview :**
  - The **Internet** is essentially a **network of networks** . It functions through multiple layers of **protocols** that build on each other, creating a **fault-tolerant global computing infrastructure** .
- **Protocols in Daily Use :**
  - Users rely on many protocols daily, often without awareness. A key protocol is **HTTP** (Hypertext Transfer Protocol), the foundational element for accessing web pages.
- **Web Beyond Hypertext :**
  - The Web extends beyond traditional **hypertext** (HTML) to include technologies like **JavaScript** , **Flash** , and **HTML5** assets (e.g., audio and video), making the term "hypertext" feel outdated.
- **Web Definitions and Evolution :**
  - The concept of the Web has evolved significantly.
    - **Web 1.0** : Characterized by static content.
    - **Web 2.0** : Represents the current era of **Rich Internet Applications (RIAs)** and increased **user collaboration** .
    - **Web 3.0** : Often associated with the **semantic web** , this future phase is anticipated to enable machines to interact with information at a granular level.
- **Web 3.0 and Semantic Web :**
  - There's no consensus on the precise meaning of **Web 3.0** , but it generally implies an evolution towards the **semantic web** .
  - The semantic web aims for machines to understand and process information as humans do, overcoming current limitations in extracting facts and making inferences from online documents.
- **Challenges :**
  - Currently, while keyword searches can yield relevant results, machines struggle to interpret and synthesize complex information found in documents without human intervention.

In summary, the chapter outlines the progression from basic web functionalities to a future where the semantic web enhances machine understanding of online content, fostering more intelligent and automated interactions.

Table 10-1: Eras of the Web and Their Characteristics

| Era/Manifestation      | Virtues                                                                                        |
|------------------------|------------------------------------------------------------------------------------------------|
| Internet               | Use of application protocols like <b>SMTP</b> , <b>FTP</b> , <b>BitTorrent</b> , <b>HTTP</b> . |
| Web 1.0                | Predominantly <b>static HTML pages</b> and <b>hyperlinks</b> .                                 |
| Web 2.0                | Focus on <b>platforms</b> , <b>collaboration</b> , and <b>rich user experiences</b> .          |
| Social Web (Web 2.x)   | Emphasis on <b>social connections</b> and <b>activities</b> in both virtual and real worlds.   |
| Web 3.0 (Semantic Web) | Contains <b>machine-understandable content</b> in large quantities.                            |

## Understanding the Semantic Web

- **Triple Structure** :
  - The semantic web uses a fundamental unit called a **triple** , which expresses facts intuitively. For example, the statement “Mr. Green killed Colonel Mustard in the study with the candlestick” can be represented as:
    - **(Subject, Predicate, Object)** : (Mr. Green, killed, Colonel Mustard).
- **Resource Description Framework (RDF)** :
  - **RDF** is the model used for defining and exchanging triples. It is:
    - **Extensible** : Allows for the creation of specialized vocabularies called **ontologies** , which provide detailed semantics for specific domains.

## Open-World vs. Closed-World Assumptions

- **Closed-World Assumption** :
  - Found in **logic programming languages** like **Prolog** . It assumes that anything not explicitly stated is **false** .
- **Open-World Assumption** :
  - Used in **RDF technology** , it treats unknown facts as **undefined** (or unknown). This means that it does not dismiss potential truths that are not directly stated.

## Summary

The semantic web aims to make information more understandable for machines, using structures like triples and RDF to express knowledge. Understanding the difference between open and closed-world assumptions helps clarify how information is interpreted within different frameworks, contributing to the development of intelligent web applications.

- **Closed-World Assumption :**

- Database systems assume that provided data is **complete** .
- Facts not explicitly stated are considered **false** .
- Merging contradictory knowledge typically results in an **error** .
- These systems are generally **non-monotonic** , meaning new information can invalidate previous facts.

- **Open-World Assumption :**

- Systems do not assume that data is complete.
- Unknown facts are treated as **undefined** rather than false.
- These systems are **monotonic** , allowing for the addition of new facts without invalidating existing ones.
- Merging disparate knowledge bases can lead to interesting challenges and opportunities.

## RDF and Open-World Framework

- **Resource Description Framework (RDF) :**

- Defined by W3C as an **open-world framework** .
- Allows anyone to make assertions about any resource without needing complete information.
- Nonsensical or inconsistent assertions are permitted.
- Application designers should build systems that can handle incomplete or inconsistent information.

## Implications of Assumptions

- Choosing between closed-world and open-world assumptions is debated among researchers.
- A closed-world assumption can lead to significant issues, especially given that web data is inherently **incomplete** .
- It's crucial to be aware of these assumptions when working with semantic web technologies.

## Inferencing with FuXi

- **FuXi** is a system that performs inference over facts.
- Languages like **RDF Schema** and **OWL** enable the expression of facts in a **machine-readable** format (e.g., (Mr. Green, killed, Colonel Mustard)).
- **Inference** is a critical step in the semantic web, allowing systems to draw conclusions from known facts.
- The concept of formal inference has roots in ancient logic (e.g., **Aristotle's syllogisms** ) and is important for **artificial intelligence** .

## Summary

Understanding the differences between closed-world and open-world assumptions is vital in the context of the semantic web. RDF supports an open-world framework, allowing flexible assertions but requiring careful design to handle incomplete data. Inferencing plays a crucial role in leveraging these facts, and systems like FuXi are integral to this process.

## FuXi: A Pythonic Inference Tool

- **FuXi :**
  - A **logic-reasoning system** designed for the semantic web.
  - Utilizes **forward chaining** to derive new information from existing facts.
  - Begins with a set of known facts and applies logical rules repeatedly until it reaches a conclusion or no new facts can be derived.
  - **Sound** : All new facts produced are true.
  - **Complete** : Any true facts can eventually be proven.
- **Deep Dive into Logic :**
  - Propositional and first-order logic are foundational concepts in FuXi's reasoning capabilities.
  - For an extensive understanding, consider reading "**Artificial Intelligence: A Modern Approach**" by Stuart Russell and Peter Norvig.

## Example of Inferencing

- **Aristotle's Syllogism :**
  - Basic example illustrating how facts lead to conclusions:
    - Given:
      - "Socrates is a man."
      - "All men are mortal."
    - Conclusion:
      - "Socrates is mortal."
- **Complex Knowledge Base :**
  - Expanded facts:
    - Socrates is a man.
    - All men are mortal.
    - Only gods live on Mt Olympus.
    - All mortals drink whisky.
    - Chuck Norris lives on Mt Olympus.
  - Question: "Does Socrates drink whisky?"
    - First deduce: "Socrates is mortal."
    - Then conclude: "Socrates drinks whisky."

## Notation3 (N3)

- **N3 Syntax :**
  - A readable and expressive format to represent facts and rules in **RDF** .
  - Popular among semantic web tools for its clarity and ease of use.

## Summary

FuXi is a powerful tool for inference in the semantic web, employing forward chaining to generate new knowledge from existing facts. Its reliability in producing sound and complete results makes it valuable for complex reasoning tasks, illustrated through examples like Aristotle's syllogism and more intricate knowledge bases. Notation3 (N3) enhances its usability by providing a clear way to express RDF data.

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## Example 10-1: Knowledge Base in Notation3

This example showcases a small knowledge base written in Notation3 (N3), which is used to express facts and rules in a machine-readable format.

- **Namespaces :**
  - **Logic Predicates :** Defined with the prefix `log` .
    - `@prefix log: .`
  - **Document Vocabulary :** Uses a custom prefix.
    - `@prefix : .`
- **Facts and Rules :**
  - **Socrates is a Man :**
    - `:Socrates a :Man.`
  - **All Men are Mortal :**
    - Rule: If `x` is a man, then `x` is mortal.
    - `{ :x a :Man } log:implies { :x a :Mortal } .`
  - **Only Gods Live on Mt Olympus :**
    - If `x` lives on Mt Olympus, then `x` is a god.
    - `{ :x :lives :MtOlympus } log:implies { :x a :god } .`
    - Conversely, if `x` is a god, then `x` lives on Mt Olympus.
    - `{ :x a :god } log:implies { :x :lives :MtOlympus } .`
  - **All Mortals Drink Whisky :**
    - Rule: If `x` is a mortal, then `x` drinks whisky.
    - `{ :x a :Man } log:implies { :x :drinks :whisky } .`
  - **Chuck Norris Lives on Mt Olympus :**
    - `:ChuckNorris :lives :MtOlympus .`

## Running FuXi

To process this knowledge base using FuXi :

- Use the command: `bash Copy code $ FuXi --rules=foo.n3 --ruleFacts`
- Ensure **FuXi** is in your path after installing it with `easy install fuxi .`

## Example 10-2: Results of Running FuXi



When running FuXi, you might see an output similar to:

plaintext Copy code

```
@prefix 7 :. @prefix rdf: . 7 :ChuckNorris a 7 :god. 7 :Socrates a 7 :Mortal; 7 :drinks 7 :whisky.
```

## Output Insights

The results indicate several conclusions that were not explicitly stated in the initial knowledge base:

- **Chuck Norris is identified as a god.**
- **Socrates is classified as a mortal.**
- **Socrates is determined to drink whisky.**

## Importance

While these deductions might seem straightforward to humans, it demonstrates the capability of machines to derive new knowledge from existing facts, showcasing the potential of semantic web technologies .

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## Key Points on Chuck Norris and the Semantic Web

### 1. Caution with Chuck Norris Facts :

- Be careful when asserting facts about Chuck Norris, even in hypothetical examples. Misrepresentations can lead to humorous or unintended consequences.

### 2. Exploring FuXi :

- If the example of using FuXi excites you, consider diving deeper into it. **FuXi** offers significant potential for exploring the **semantic web** .
- The semantic web is more complex and advanced than the **social web** and is a valuable area of study, especially regarding inference from social data.

### 3. Blurry Divide Between Webs :

- While this book has not focused heavily on the semantic web, the line between the **social web** and **semantic web** is blurred and constantly changing.
- The growth of social data on the web, along with initiatives like **microformats** from various organizations and **Facebook's Open Graph** , is pushing the development of a semantic web.

### 4. Potential of Social Data :

- The increase of social data can accelerate the creation of a semantic web that allows for intelligent actions by agents on our behalf. Although we are not fully there yet, the possibilities are promising.

### 5. Hopeful Outlook :

- Embrace a hopeful perspective about the future of the semantic web. Reflect on Epicurus's wisdom: appreciate what you currently have, as it was once just a hope for the future.

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## Index Notes

- **3D Graph Visualization** : Interactive visualizations discussed on page 116.
- **80-20 Rule (Pareto Principle)** : A concept highlighted in the introduction (xiii) and elaborated on in context (300).
- **@ (At Symbol)** : Used to denote Twitter usernames (11).

## A

- **Access Token** :
  - For Facebook desktop apps, detailed on pages 272-278.
  - Specific access tokens for Facebook applications are addressed on page 272.
- **ActivePython** : Mentioned as a tool (1).
- **Address-Book Data** : Exporting LinkedIn connections is discussed (169).
- **Agglomerative Clustering** : Techniques explored on page 185.
- **Ajax Toolkits** : Tools for web applications discussed on page 183.
- **Analytics** :
  - Quality in **entity-centric analysis** is analyzed (267-269).
- **API Calls** :
  - Rate limits for Twitter API calls are detailed (10).
- **Aristotle** : References to **sylogisms** (317).
- **Association Metrics** : Discussed in various contexts (175, 230).
- **Authentication** : General principles covered (84). See also **OAuth** .

## B

- **B-Trees** : Data structures covered on page 60.
- **BeautifulSoup** : A library for web scraping mentioned (23).
- **Berners-Lee, Tim** : Key figure in web development, noted (xv).

- **BigramAssociationMeasures Class** : Explored in detail (175).
- **BigramAssocMeasures Class** : Discussed in context (226).
- **Bigrams** :
  - Key concepts related to collocations, contingency tables, and scoring functions (224-231).
  - Computing bigrams using **NLTK** (225).
- **Binomial Distribution** : Covered in the context of statistics (230).
- **Blogs** :
  - Techniques for data harvesting from blogs discussed (239).
  - Example of summarizing a Tim O'Reilly Radar blog post (252).
  - Using NLTK tools for parsing blog data (246).
- **Branching-Factor Calculations** : Related to graphs of varying depths (29).
- **Breadth-First Techniques** :
  - Brief analysis provided (28).
  - Usage in crawling XFN links discussed (25).
- **Browsers** :
  - Chrome and its **Graph Your Inbox Extension** (81).
  - Support for the **canvas element** (301).
- **Buzz** : Refers to Google Buzz in context.
- **Buzz Module** : Discussed in the context of data (204).

## C

- **Cantor, Georg** : Noted for contributions to mathematics (95).
- **Canvas Element** : Browser support discussed (301).
- **Canviz Tool** : Mentioned as a tool for visualizations (17).
- **Cardinality of Sets** : Explored in mathematical context (95).
- **Chi-Square** : Statistical method discussed (231).
- **Chunking** : A concept in natural language processing (244).
- **Chunks** : Related terminology (242).
- **Circo Tool** : Another visualization tool mentioned (15).

For suggestions on improving the index, feedback can be sent to [index@oreilly.com](mailto:index@oreilly.com).

- **Cliques** :
  - Detecting and analyzing cliques in Twitter friendship data (110–113).
- **Closed-World vs. Open-World Assumptions** :
  - Discussed in the context of reasoning and data interpretation (316).
- **Cluster Module** :
  - Used for clustering techniques (185).
- **Clustering** :
  - **Common Similarity Metrics** : Various metrics for clustering discussed (174).
  - **Contacts by Job Title** : Clustering contacts based on job titles (172).
  - **Hierarchical Clustering** : Techniques covered (185).
  - **Improving Performance** : Incorporating random sampling for better performance (182).
  - **Intelligent Clustering** : Enhancing user experiences (183).
  - **K-Means Clustering** : Detailed on (187).
  - **LinkedIn Network** : Clustering geographically (193).
  - **Mapping Techniques** :
    - Using **Dorling Cartograms** (198).
    - Mapping with **Google Earth** (194–197).
  - **Scalability** : High cost associated with scaling (181).
  - **Tutorial on Clustering Algorithms** : Found on (188).
  - **Cosine Similarity** : Using cosine similarity to cluster posts (219–221).
  - **Greedy Approach** : A method used in clustering (178).
- **Code Examples** : Reference to code examples throughout the book (xv).
- **collections.Counter Class** : Introduced for counting hashable objects (9).
- **Collocations** :
  - Definition and computation discussed (224).
  - Using NLTK for computing collocations (225).
- **Contingency Tables** :
  - Definition and examples provided (226).
  - Scoring functions related to contingency tables (228–231).
- **Cosine Similarity** :
  - Theory and limitations discussed (217).
  - Application in clustering posts (219–221).
- **CouchDB** :
  - Overview from pages 48-67, covering:
    - Aggregate view of test databases (49).
    - Use of **B-Tree Data Structure** (60).
    - Bulk loading documents (51).
    - Configuring for **CouchDB-Lucene Awareness** (64).
    - Document analysis and frequency analysis (48, 55).
    - RESTful API for accessing data (63).
    - Sorting documents by various criteria (53, 61).
    - Map/reduce functionality utilization (52).
- **CouchDB-Lucene** :
  - Querying tweet data and full-text indexing (133, 64–67).
- **Counter Class** : Reference again for counting (9).
- **cPickle Module** : Used for serializing Python object structures (8).
- **Cross-Validation** : Discussed in the context of model evaluation (269).
- **CSV (Comma-Separated Values) Files** :

- Mentioned for normalizing LinkedIn contact data (169).
- Related to data exporting (169).

## D

- **Data Hacking Tutorial** :
  - A guide on collecting and manipulating Twitter data (1–17).
  - Topics include frequency analysis and visualizing tweet graphs (4–15).
- **Dateutil Package** : Used for date manipulations (54).
- **Degree of a Node** : Definition related to graph theory (13).
- **Demo Function (NLTK Modules)** : Example functions from NLTK for demonstration (206).
- **Dendogram** : Visualization of LinkedIn contacts clustered by job title (187).

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## Detailed Notes

- **Design Documents (CouchDB)** :
  - Overview of design documents on page 53.
  - Used for managing views and functions in CouchDB.
- **Inspecting in Futon** :
  - Tools for visualizing and inspecting databases (55).
- **Dice's Coefficient** :
  - A metric for comparing the similarity between two sets, used in various analyses (230).
- **Difference Operations** :
  - Explored in the context of set theory (94).
- **Digraphs** :
  - Directed graphs, foundational for understanding relationships (10).
- **Dirty Records** :
  - Refers to incomplete or inaccurate data entries (169).
- **Distance Metrics (NLTK)** :
  - Used to measure similarity between items:
    - **Jaccard and MASI Distances** : Comparison of these metrics on two sets (177).
    - Useful for comparing small sets of items (176).
- **Distributions** :
  - Illustrating the degree of each node in a graph (13).
- **Document-Centric Data** :

- Analysis focused on documents within databases (49).
- **Documentation :**
  - Resources for Python and Twitter API are available (xvii, 5).
- **Documents :**
  - **Finding Similar Documents :** Techniques discussed (217–222).
  - **Clustering Posts :** Using cosine similarity (219–221).
  - **Vector Space Models :** Relation to cosine similarity (217–219).
  - **Visualizing Similarity :** Graphical representation methods (222–224).
  - **Summarizing Techniques :** Analysis of Luhn’s algorithm (255–257).
- **Dojo Tree Widget :**
  - Produces JSON for consumption and data transformation (183, 184).
- **Dorling Cartograms :**
  - Used for mapping professional networks, including LinkedIn (193, 198).
- **DOT Language :**
  - Utilized for graph description (14).

## E

- **Easy install :**
  - Tool for installing Python packages (2).
- **Edit Distance :**
  - A metric for measuring how different two strings are (175).
- **Ego Graphs :**
  - Graphs centered around a particular individual (15).
- **End of Sentence (EOS) Detection :**
  - Techniques for detecting sentence boundaries (241, 242).
- **Entity Extraction :**
  - Process of identifying and categorizing key elements from text (259).
- **Entity-Centric Analysis :**
  - Focused on discovering interactions between entities and the quality of analytics (258–269).
- **Epicurus :**
  - Referenced for philosophical insights (319).
- **Erlang Programming Language :**
  - Noted for its support of concurrency (51).
- **Extended Permissions (Facebook) :**
  - Discussed in the context of OAuth and user permissions (276).
- **Extraction :**
  - Techniques for data extraction from various sources (244).

## F

- **Facebook :**
  - A comprehensive section (271–311) covering:
    - **Authentication Documentation** : Guidelines for accessing APIs (276).
    - **Developer Principles and Policies** : Overview of requirements (271).
    - **OAuth 2.0 Access Token** : Steps to obtain a token for desktop apps (272–278).
    - **Open Graph Protocol** : Framework for integrating Facebook data (21).
    - **Query APIs** : Details on querying Facebook's APIs (278–289).
    - **Graph API Exploration** : How to navigate connections within Facebook (282–285).
    - **FQL Queries** : Writing and executing Facebook Query Language queries (286–289).
    - **Network Visualizations** : Various methods for visualizing Facebook data (289–311).
- **Fail Whale :**
  - Term used to describe Twitter outages (88).
- **False Negatives (FN) and False Positives (FP) :**
  - Metrics for evaluating the accuracy of data (268).
- **Feedparser Module :**
  - Used for parsing RSS and Atom feeds (245).
- **findall() :**
  - Function in Python for finding all matches of a pattern (11).
- **FOAF (Friend of a Friend) :**
  - A vocabulary for describing people and their relationships (20).
- **Folksonomy :**
  - User-generated categorization system (144).
- **Food Network :**
  - Mentioned in relation to data and social media interactions (35).
- **Forward Chaining :**
  - A reasoning technique used to infer new information from existing facts (317).
- **FQL (Facebook Query Language) :**
  - A specialized language for querying Facebook data (278).

## Detailed Notes

- **Encapsulating FQL Queries :**
  - **Python Class** : Use a small class to manage FQL queries effectively (287).
  - **Multiquery** : Techniques for executing multiple queries at once (286).
- **Gathering Data for RGraph :**
  - Queries designed to collect data, including names, locations, and hometowns of friends (304).
  - Specific queries to support visualization needs (291).
- **Frequency Analysis :**

- Conducted on various datasets, including Twitter data using NLTK (9).
- **Map/Reduce Inspired** : Leveraging CouchDB for frequency analysis (55–67).
  - Frequency analysis categorized by date/time range (56–60) and sender/recipient (60).
- **TF-IDF (Term Frequency-Inverse Document Frequency)** :
  - Method for evaluating the importance of a word in a document relative to a collection (209–216).
  - Used for querying Buzz data (215).
- **Buzz Data Analysis** :
  - Frequency distributions of terms in Buzz data samples (208).
  - Unigrams and bigrams analyzed within texts (228).
- **Friend of a Friend (FOAF)** :
  - Framework for describing relationships among people (20).
- **Friend/Follower Metrics** :
  - Techniques to calculate a Twitter user's most popular follower (105) and analyze connections (103).
  - Finding common friends or followers across multiple Twitter accounts (102).
  - Identifying tweet entities that are also friends (131).
- **Friendship Analysis** :
  - Conducting FQL queries on Facebook to gather data for visualizing mutual friendships within groups (301–304).
  - **Where Have My Friends All Gone?** : A data-driven game concept utilizing this analysis (304–309).
- **Full-Text Indexing** :
  - Utilizing the **Lucene Library** with CouchDB for full-text indexing (63).
  - Implementing couchdb-lucene for enhanced querying capabilities (64–67).
- **Futon** :
  - A tool for inspecting design documents and viewing CouchDB document collections (49, 55).
- **FuXi** :
  - A powerful tool for logical inference in semantic web applications.
  - Running FuXi from the command line allows for processing a knowledge base to derive new facts (318).

## G

- **GAE (Google App Engine)** :
  - Used for deploying web applications, with reference to Facebook authentication (272).
- **Generator Functions** :
  - Employed in Python for efficient data handling (55).
- **Geo Microformat** :
  - Method for embedding geographical data in web pages (20, 30–34).
  - Example: Extracting geo data from services like MapQuest (31) and plotting it with Google Maps (32).
- **Geographical Clustering** :
  - Techniques for clustering LinkedIn networks geographically (193–199).
  - Visual mapping using Dorling Cartograms (198) and Google Earth (194–197).
- **Geopy Module** :
  - A Python library for geographical calculations and mapping (194).
- **Getmail** :
  - A tool for retrieving emails (80).
- **GitHub Repository** :
  - Centralized place for code and project collaboration (xv).



- **Gmail :**
  - Accessed using OAuth for secure login (232).
  - Techniques for fetching and parsing email messages (233–235).
- **Google :**
  - **Social Graph API :** A tool for understanding relationships between users (30).
  - Overall platform statistics, including total monthly visits (271).
  - **Xoauth Implementation :** A method for integrating OAuth with Google services (232).
  - **Google Buzz :** Social media platform for sharing updates and analyzing interactions (201).
  - Techniques for bigram analysis, clustering posts, and visualizing data similarities (224–231).

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## Detailed Notes

- **Google Earth :**
  - Used for **mapping your LinkedIn network** (194–197), allowing for visual representation of professional connections.
- **Google Maps :**
  - A tool for displaying geographical data and locations (33).
- **Graph API (Facebook) :**
  - Documentation and methods for interacting with Facebook's Graph API (278).
  - Explore connections one at a time (282–285).
- **Graph Your Inbox Chrome Extension :**
  - Tool for visualizing email interactions (81).
- **Graphs :**
  - **Creating Graphs :**
    - **Retweet Data :** Visualizing retweet relationships (12).
    - **NetworkX :** Creating graphs with nodes and edges (3).
    - **Interactive 3D Graph Visualization :** Used for advanced data representation (116).
    - Visualizing similarity between items (221).
- **Graphviz :**
  - Tool for rendering graphs, with online documentation available (15).
  - Downloading and installing instructions (14).
  - Shows connections, such as trends around #JustinBieber and #TeaParty (165).
  - Circular layout for Twitter search results (15).
  - **GVedit :** A graphical editor for Graphviz (15).
- **Greedy Heuristic for Clustering :**
  - An approach to improve clustering efficiency (178).
- **Hadoop :**
  - A framework for distributed data processing (237).
- **Hashtags :**
  - **Counting Entities :** Analyzing hashtag occurrences in tweets (144).

- Frequency analysis in specific tweets, such as those containing #JustinBieber or #TeaParty (153).
- **Microformats :**
  - **hCalendar, hCard, hRecipe, hResume, hReview** : Standard formats for structuring data (20).
  - **Parsing Data** : Techniques for extracting data from structured formats (35, 37).
- **HTML :**
  - Fundamentals of web pages and hyperlinks (Web 1.0) (314).
  - **Semantic Markup** : Enhances data meaning (21).
  - Sample geo markup for geographical data (30).
  - Displaying tag clouds in templates (161).
- **HTTP :**
  - Used for web communication (314).
  - Methods for acting on URIs (49).
  - Errors encountered in Twitter interactions (88).
- **Identity Consolidation :**
  - Integrating user identities across platforms (30).
- **IDF (Inverse Document Frequency) :**
  - Part of the TF-IDF framework, crucial for determining the significance of words (209).
  - IDF calculation methods (211).
- **IETF OAuth 2.0 Protocol :**
  - Standards for secure API authentication (86).
- **IMAP (Internet Message Access Protocol) :**
  - Used for accessing emails via OAuth (232).
  - Constructing IMAP queries for retrieving emails (233).
- **Inference :**
  - Application in machine knowledge and logic programming (317).
  - Important for reasoning within RDF and programming languages (315).
- **Influence Measurement :**
  - Techniques for assessing Twitter users' influence (103–108).
  - Calculating the most popular followers and analyzing connections (105, 104).
- **Infochimps and Strong Links API :**
  - Tools for data retrieval and analysis (114–116).
- **Information Retrieval Industry :**
  - The sector focused on data organization and retrieval (236).
- **Intelligent Clustering :**
  - Advanced clustering techniques for user experiences (183).
- **Interactive 3D Visualization :**
  - Tools for creating engaging visual representations of data (116).
  - Tag clouds for entities related to trending topics like #JustinBieber and #TeaParty (161).
- **Interpreter :**
  - The Python interpreter (IPython) for running scripts and analyzing data (17).
- **Intersection Operations :**
  - Analyzing overlap between different tweet entities (94, 156).

## Detailed Notes

- **Finding Similar Documents :**
  - Use **cosine similarity** to determine how similar documents are based on their vector representations (219–221).
- **TF-IDF (Term Frequency-Inverse Document Frequency) :**
  - **Introduction** : A statistical measure used to evaluate the importance of a word in a document relative to a collection (209–215).
  - **Querying Buzz Data** : Apply TF-IDF to extract relevant information from Buzz data (215–216).
  - **Vector Space Models** : Used in conjunction with cosine similarity to represent documents as vectors (217).
- **Irrational Numbers :**
  - Defined as numbers that cannot be expressed as a fraction of two integers (95).
- **Jaccard Distance :**
  - **Definition** : A metric for comparing the similarity and diversity of sample sets (176).
  - **Comparison** : It can be compared to **MA SI distance** for understanding similarities between two sets (177).
  - **Jaccard Index** : Another measure of similarity defined (230).
- **Java-Based Search Engine Library (Lucene) :**
  - A popular library used for implementing search functionality (63).
- **JavaScript :**
  - **Indexing Function** : Built on JavaScript, used for web applications (66).
  - **Map/Reduce Functions** : Employed in CouchDB for data processing (53).
- **JIT (JavaScript InfoVis Toolkit) :**
  - Used for creating interactive visualizations, such as RGraph visualizations of Facebook networks (290–294) and Sunburst visualizations (296).
- **Job Titles :**
  - **Clustering Contacts** : Organizing LinkedIn contacts based on job titles (172–188).
  - **Standardization** : Importance of standardizing job titles to avoid discrepancies (170).
  - **Common Similarity Metrics** : Used in clustering analysis (174–177).
  - **Clustering Techniques** :
    - **Greedy Approach** : A method to improve clustering efficiency (178).
    - **Hierarchical Clustering** : Groups contacts based on similarity (185).
    - **K-Means Clustering** : Another clustering method applied (187).
  - **Problems** : Issues with job title standardization and its impact on data accuracy (170).
- **JSON (JavaScript Object Notation) :**
  - **Data Format** : A lightweight format for data interchange (184).
  - **Examples** : Producing JSON for Dojo's Tree widget and converting mbox data (45, 304).
  - **Pretty-Printing** : Formatting Twitter data into a readable JSON format (5).
- **JVM (Java Virtual Machine) :**
  - Platform for running Java applications (63).
- **K-Means Clustering :**
  - A specific algorithm used for grouping data based on characteristics (187).
- **Keyword Search :**
  - Essential for applications to allow users to find specific data efficiently (63).
- **KML (Keyhole Markup Language) :**

- Used for representing geographic data for Google Earth (33).
- **Levenshtein Distance :**
  - A measure of how many single-character edits are needed to change one word into another (175).
- **Lexical Diversity :**
  - A measure of how varied the vocabulary is within a text (7).
- **Likelihood Ratio :**
  - A statistical measure used to assess the strength of evidence (230).
- **LinkedIn :**
  - Techniques for clustering and analyzing LinkedIn contacts by job titles and geographical data (167–199).
  - **Mapping Techniques :** Using tools like Dorling Cartograms and Google Earth for visualizing connections (198, 194–197).
  - **API Usage :** Steps for developer signup and fetching profile information (188–193).
  - **Normalization :** The process of standardizing data, such as company names and job titles (169).
- **Lucene :**
  - A powerful library for text searching and indexing (63). Techniques for scoring documents are part of its functionality (67).
- **Luhn, H.P. :**
  - Known for his analysis of summarization algorithms (256).

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## Detailed Notes

- **Mail Events Visualization :**
  - Use **SIMILE Timeline** to visualize mail events, providing a chronological representation (77–80).
- **Mail Headers :**
  - Extended mail headers can be viewed through email clients, allowing for deeper analysis (44).
- **Mail Trends Project :**
  - An initiative aimed at analyzing trends in email usage and communication (67).
- **Mailboxes :**
  - A focus on analyzing your own mail data and understanding email interactions (41–82).
  - **Graph Your Inbox Chrome Extension :** A tool for visualizing inbox data (81).
  - Analysis techniques involve using **mbox** format and CouchDB for data handling (48–67).
- **Email Analysis :**
  - Bulk loading documents into **CouchDB** for efficient data management (51).
  - **CouchDB-Lucene** enables full-text indexing for searching through email data (63–67).
  - **Map/Reduce-inspired Frequency Analysis :** Techniques for counting messages by sender/recipient and by date (55–61).
  - **Sensible Sorting :** Approaches for organizing documents logically (53–55).
- **Mbox :**
  - A file format for storing email messages, essential for analysis (41–48).

- Includes converting mbox data to **JSON** for easier data manipulation (45).
- **Threading Conversations** : Utilizing jwz threading to create structured discussion threads from emails (67–77).
- **Map/Reduce** :
  - Utilizes CouchDB capabilities to analyze mail data (49).
  - Example tasks include counting messages and organizing them by date (60, 56–60).
- **Mapping Techniques** :
  - **LinkedIn Network Mapping** : Use **Dorling Cartograms** and **Google Earth** for visualizing professional connections (198, 194–197).
  - **Geo Data Extraction** : Extract geo data from resources like **MapQuest Local** and Wikipedia articles (31, 30).
- **MA SI Distance** :
  - A metric for comparing sets of items, defined alongside Jaccard distance (176, 177).
- **Mavens** :
  - Influential individuals in a network who help spread information (103).
- **Metadata** :
  - **OGP Query** : Metadata delivered in response to Open Graph Protocol queries (280).
  - **Microformats** : A way to embed structured data into web pages, enhancing data accessibility (19).
  - **Geo Microformats** : Specific formats for extracting and utilizing geo data (30–34).
- **N-Gram Similarity** :
  - A method for comparing the similarity between text sequences, using n-grams as the basis (175, 224).
- **Natural Language Processing (NLP)** :
  - Techniques and tools used for processing and analyzing natural language data, specifically through the **Natural Language Toolkit (NLTK)** .
- **NetworkX** :
  - A Python library for creating and analyzing complex networks, such as building graphs to represent retweet data and exporting friend/follower data for analysis (12–14, 108).
  - Essential for finding cliques in Twitter friendship data and understanding social connections (111, 3).

This concise organization of information retains essential details while ensuring clarity and accessibility.

## Detailed Notes

- **Nix (Linux/Unix) Environment** :
  - Refers to systems based on Linux and Unix, providing a versatile platform for development and data analysis (xvi).
- **NLP (Natural Language Processing)** :
  - **Entity-Centric Analysis** : Focus on analyzing entities within texts to extract meaningful insights (258–269).
  - **Quality of Analytics** : Emphasizes the importance of reliable analytics in NLP processes (267).
  - **Sentence Detection in Blogs** : Utilizing **NLTK** for identifying sentences in blog posts (245–249).

- **Document Summarization** : Techniques for condensing documents into key points (250–257).
  - **Luhn’s Algorithm** : A specific method for summarization that analyzes term frequency (256).
- **Syntax and Semantics** : Understanding the structure (syntax) and meaning (semantics) of language (240).
- **Typical NLP Pipeline with NLTK** : Steps involved in processing natural language using the NLTK toolkit (242–245).
- **NLTK (Natural Language Toolkit)** :
  - A powerful Python library for NLP, covering various functionalities (8, 202).
  - **Bigrams and Frequency Analysis** : Computing bigrams and performing frequency analysis with the toolkit (175, 9).
  - **Stopwords** : Downloading and managing common words that may be excluded from analysis (208).
  - **Entity Extraction** : Identifying and extracting entities from text (259).
  - **Hacking Google Buzz Data** : Using NLTK for analyzing data from Google Buzz (206).
  - **Sentence Detection** : Implementing methods for detecting sentences in texts (245–249).
  - **NLTK Functions** :
    - `nlk.batch_ne_chunk` : For named entity recognition (260).
    - `nlk.cluster.util.cosine_distance` : Used for measuring similarity (219).
    - `nlk.metrics.association` : A module for calculating association measures (175).
    - **POS Tagging** : Assigning part-of-speech tags to words in a sentence (243).
- **OAuth** :
  - **Access Protocols** : Used for accessing various services like Gmail (IMAP and SMTP) and Facebook (272–278).
  - **IETF OAuth 2.0** : A standard for authorization, with major steps summarized (86).
  - **LinkedIn OAuth** : Templates and methods for extracting and using OAuth verifiers (192).
- **Open Graph Protocol (OGP)** :
  - A framework for sharing data across social platforms, allowing for rich data querying and responses (21, 278).
  - **RDFa** : Sample responses and metadata used in OGP queries (279, 280).
- **Pareto Principle (80-20 Rule)** :
  - A principle stating that roughly 80% of effects come from 20% of causes, relevant in data analysis and decision-making (xiii, 300).
- **POP3 (Post Office Protocol version 3)** :
  - A protocol used for retrieving emails, essential for email applications (80).
- **Power Law** :
  - A statistical distribution often observed in network data, where a small number of nodes have a high degree of connections (13).
- **Profiles** :
  - Accessing and fetching extended profile information from social media platforms like Facebook and LinkedIn (276, 188–193).
- **Prolog and Logic-Based Languages** :
  - Prolog is a logic-based programming language often used for AI and NLP applications (315).

These notes provide a concise yet comprehensive overview of key concepts in NLP and related technologies, facilitating easier understanding and retention.

## Detailed Notes

- **Encapsulating FQL Queries with Python :**
  - Creating a **Python class** to manage and simplify the use of **FQL (Facebook Query Language)** queries for better organization and reuse (287).
- **Inferencing about Open World with FuXi :**
  - Using **FuXi** , a reasoning engine, to make inferences in an **open-world** scenario, which assumes that not all knowledge is known (317).
- **Installing Development Tools :**
  - Initial steps for setting up necessary **development tools** for programming (1).
- **List Comprehension :**
  - A concise way to create lists in Python, enhancing code readability and efficiency (6).
- **Map/Reduce Functions for CouchDB :**
  - Implementing **map/reduce functions** in **CouchDB** to process and analyze large datasets (53).
- **Support for Sets :**
  - Understanding and utilizing **set operations** within programming, particularly in Python (94).
- **Tutorial Overview :**
  - A brief introduction to the topics and concepts covered in the tutorial (3).
- **Python SDK for the Graph API :**
  - Using the **Python Software Development Kit (SDK)** to interact with the **Facebook Graph API** , facilitating data retrieval and manipulation (282).

## Q

- **Quicksort Algorithm :**
  - An efficient sorting algorithm used for organizing data (61).
- **Quopri Module :**
  - A Python module for encoding and decoding **quoted-printable text** , commonly used in email transmissions (47).

## R

- **Radial Tree Layout :**
  - A visual representation of **LinkedIn contacts** organized by job title using a radial tree format (187).
- **Rate-Throttling Limits (LinkedIn) :**
  - Restrictions imposed by LinkedIn on the frequency of API requests to ensure fair usage (193).
- **Rational Numbers :**
  - Numbers that can be expressed as a fraction of two integers (95).
- **Raw Frequency :**
  - The basic count of occurrences of a term or entity within a dataset (230).

• **RDF (Resource Description Framework) :**

- **RDF (Resource Description Framework) :**
  - A framework for representing information about resources on the web, supporting structured data (315).
  - **Notation3** : A method for expressing RDF data (317).
  - **RDF Schema** : A vocabulary description for RDF (317).
  - **RDFa** : Metadata format for embedding in web pages, useful for search engine optimization (20).
- **Re Module :**
  - A Python module that provides tools for **regular expressions** , allowing for complex text search and manipulation (11).
- **Recall :**
  - A measure of how many relevant instances were retrieved in information retrieval tasks (267).
- **Recipes and Reviews in Microformats :**
  - Utilizing **microformats** to represent recipes and their reviews, enhancing data sharing (35–39).
- **Redis :**
  - A data structure store often used for caching and real-time data storage (92).
  - **Exporting Data to NetworkX** : Facilitating the analysis of data within graph structures (108).
  - **Randomkey Function** : A Redis function to retrieve a random key from the database (103).
  - **Sinterstore Function** : A function for performing intersection operations on sets in Redis (102).
- **Regular Expressions :**
  - Patterns used for matching text, such as finding retweets (11).
- **REST-Based Interface for CouchDB :**
  - Provides a way to interact with CouchDB using standard HTTP methods (49).
- **RESTful APIs :**
  - APIs that follow REST principles for web services, including those for **Google Buzz** and **Twitter** (204, 84).
- **Results Query (FQL) :**
  - A specific type of query in FQL to retrieve data (286).
- **Retweeting :**
  - The act of sharing another user's tweet, often tracked for analysis (10).
  - **Counting Retweets** : Analyzing how often a user's tweets are shared (138).
  - **Finding Frequent Retweeters** : Identifying users who commonly retweet specific topics or hashtags (142, 155, 154).
  - **Graph of Retweets** : Visualizing the relationships of who retweeted whom (12).
- **RGraphs :**
  - Visualizations of networks, specifically for analyzing Facebook interactions (290–294).
- **Rich Internet Applications (RIAs) :**
  - Web applications that provide a more interactive user experience (314).
- **Rotating Tag Cloud :**
  - A dynamic visualization of tags used in Facebook wall data, representing popularity (309–311).
- **RT (Retweet) Token :**
  - A specific token used in tweets to denote that they are retweets (10).

## S

- **Sample Error :**
  - The error involved in estimating population parameters from sample data (267).
- **Scalable Clustering :**



- Techniques for clustering data that can efficiently handle larger datasets (181).
- **Scalable Force Directed Placement (SFDP) :**
  - A method for arranging nodes in a network visually based on their connections (165).
- **Scoring Functions :**
  - Functions used to evaluate the relevance or importance of items in data analysis (229).
- **Screen Names :**
  - Identifiers used by users on social platforms, often resolved from user IDs (93, 99).
- **Search API (Twitter) :**
  - An API provided by Twitter for querying and retrieving tweets (5).
- **Search Engines :**
  - Tools that index and retrieve information from the web (236).
- **Semantic Markup :**
  - HTML markup that conveys meaning and context to data, enhancing search engine understanding (21).
- **Semantic Web :**
  - A vision for a web of data that can be processed by machines, allowing for better data integration and retrieval (313–319).
  - **Open-World vs. Closed-World Assumptions** : Differences in how knowledge is treated, relevant for data inference (316).
- **Semantics :**
  - The study of meaning in language, crucial for NLP (313).
- **Semi-Standardized Relational Data :**
  - Data that follows some standardization but still allows for variations (169).
- **Sentence Detection in Blogs :**
  - Using NLTK to identify sentences within blog content (245–249).
  - **Sentence Tokenizer** : A tool for breaking text into sentences (248).
- **Set Operations :**
  - Mathematical operations involving sets, such as intersections and unions, applicable in data analysis (94).
  - Examples include analyzing overlaps between entities in tweets (156).

These notes simplify and clarify the key concepts, making them easier to understand while maintaining important details.

## Detailed Notes

- **SFDP (Scalable Force Directed Placement) :**
  - A technique for visually arranging nodes in a graph based on their connections, allowing for scalable visual representations (165).
- **Similarity Metrics :**

- **Common Metrics for Clustering** : Techniques used to determine how similar data points are (174).
- **Cosine Similarity** : A popular method for measuring the angle between two vectors in a multi-dimensional space, used in clustering posts (217).
- **Limitations** : Despite its usefulness, cosine similarity has drawbacks, especially in certain contexts (236).
- **Vector Space Models** : The theoretical foundation for how similarity metrics, including cosine similarity, operate (217).
- **Visualizing Similarity** : Graphs can illustrate relationships and similarities between data points, enhancing understanding (221).
- **Social Graph APIs** :
  - **Twitter's APIs** : Provide tools for accessing social network data, detailed in online documentation (90).
  - **Social Web** : Refers to platforms and technologies that enable social interaction online (314).
  - **SocialGraph Node Mapper** : A tool for visualizing relationships within social graphs (30).
- **Sorting Documents** :
  - Techniques for **sorting documents by value** in analysis (61) and within **CouchDB** (53).
- **Text Tokenization** :
  - Using the **split method** to break text into smaller units, facilitating analysis (206, 237).
- **Visualizing Data** :
  - **Spreadsheets** : Can be used to display and analyze Facebook network data visually (298).
  - **Tag Clouds** :
    - Used for visual representation of terms based on frequency, including design considerations for crafting effective tag clouds (161).
    - Examples include interactive 3D tag clouds for tweets related to specific hashtags (#JustinBieber, #TeaParty) (161).
    - Also utilized to visualize Facebook wall data as rotating tag clouds (309–311).
- **Statistical Models in Natural Language Processing** :
  - Employed for processing and analyzing language data (269).
  - **Stemming Verbs** : Reducing words to their root forms to improve text analysis (216).
- **Stopwords** :
  - Common words (like "and," "the") that are often filtered out in text processing to enhance analysis (208, 256).
- **Streaming API (Twitter)** :
  - A real-time API allowing access to live tweet data (123).
- **Strong Links API** :
  - An API for analyzing connections and relationships between users (114–116).
- **Statistical Analysis** :
  - **Student's T-Score** : A statistic used to determine if there is a significant difference between two sets of data (231).
  - **Subject-Verb-Object Triples** : A foundational structure in understanding sentence semantics (261, 315).
- **Document Summarization** :
  - Techniques for creating concise summaries of longer texts (250–257).
  - **Luhn's Algorithm** : An analysis method for document summarization (256).
- **Text Mining** :
  - Involves extracting useful information from large volumes of text (201–237).
  - Key concepts include:
    - **Bigrams** : Pairs of words analyzed together (224–231).
    - **Collocations** : Identifying commonly occurring word combinations (228).
    - **Data Hacking with NLTK** : Using the Natural Language Toolkit for data analysis (206).
- **TF-IDF (Term Frequency-Inverse Document Frequency)** :
  - A numerical statistic used to reflect how important a word is to a document in a collection (209–215).
  - Useful for querying data, including Google Buzz, to find relevant documents (215–216).
  - Limitations exist in its application alongside cosine similarity (236).
  - **Calculating Cosine Similarity** : Involves using TF-IDF vectors to measure document similarity (219).

## Detailed Notes

- **Limitations of Data Analysis** : Discusses challenges encountered when analyzing data (236).
- **Querying Google Buzz Data** : Involves extracting information from Google Buzz using specific techniques (215–216).
- **Thread Pools** :
  - **Definition** : A thread pool is a collection of threads used to manage concurrent tasks effectively.
  - **Maximizing Read Throughput** : Using thread pools can enhance read performance from **CouchDB** (70).
- **Threading Conversations** :
  - **From mbox Data** : Techniques for grouping email threads together for better analysis (67–77).
  - **Tweet Discussion Threads** : Analyzing Twitter conversations by linking related tweets (135–138).
- **Tokenization** :
  - **Definition** : The process of breaking text into smaller units (tokens), such as words or phrases.
  - **Examples** :
    - **Mapper for Tokenization** : A component that divides documents into tokens for analysis (63).
    - **Using NLTK** : The **Natural Language Toolkit** provides various tokenization methods, including the **TreebankWord Tokenizer** (248).
    - **Split Method** : Another technique for tokenizing text (206, 237).
- **Trends and Twitter Search** : Techniques for analyzing trending topics on Twitter (5).
- **True Positives (TP) and True Negatives (TN)** : Key metrics for evaluating the performance of classification algorithms (268).
- **Turing Test** : A measure of a machine's ability to exhibit intelligent behavior equivalent to, or indistinguishable from, that of a human (240).
- **Tutorials** :
  - **Getting Started with Timeline** : A guide for using timeline features in data visualization (79).
  - **Official Python Tutorial** : Resources for learning Python (3).
  - **Tutorial on Clustering Algorithms** : Educational material on how to implement clustering techniques (188).
- **Tweet Analysis** :
  - **Analyzing One Entity at a Time** : Focused analysis on individual tweets (123).
  - **Counting Hashtag Entities** : Methods to quantify hashtag usage in tweets (144).
  - **Retweet Analysis** :
    - Counting retweets for individual users (138).
    - Identifying tweets that are most frequently retweeted (142).
    - Finding frequent retweeters for hashtags like **#JustinBieber** and **#TeaParty** (155, 154).
  - **Harvesting Tweets** : Collecting tweets on specific topics or hashtags (147).
- **Visualizing Tweet Data** :
  - Techniques for displaying community structures and relationships within tweet data using tag clouds (158) and other visual methods (162–166).

- **Twitter Data Collection :**

- **Authenticating with OAuth :** Required for accessing Twitter data securely (88).
- **Friend/Follower Metrics :** Basic statistics related to user connections on Twitter (96).
- **Extracting Relationships :** Analyzing connections within tweet data, including frequency analysis using NLTK (9).
- **Resolving Usernames :** Techniques to convert user IDs into screen names (99).

- **Using Redis :** A database tool for managing data related to Twitter analysis (92).

- **RESTful API and Twitter :** Interactions with Twitter's API, including extracting and visualizing data (84).

These notes clarify key concepts while preserving essential details for better understanding.

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## Detailed Notes

- **twitter.oauth Module :** A module for handling OAuth authentication with Twitter (90).
- **TwitterHTTPError Exceptions :** Errors encountered when making HTTP requests to the Twitter API (88).
- **twitter `search` .trends()** : Function used to retrieve trending topics on Twitter (5).
- **twitter `text` Package :** A package for analyzing and processing text from Twitter (121).

## U

- **Ubigraph :** A tool for visualizing graphs interactively (116).
- **UnicodeDecodeError :** An error that occurs when there is an issue decoding Unicode text (45).
- **Unigrams :** Single words or tokens used in text analysis (228).
- **Union Operations :** Set operations that combine data sets, often used in data analysis (94).
- **URLs :** Uniform Resource Identifiers that provide a way to identify resources on the web. They interact with HTTP methods (49).
- **URLs :**
  - **Resolving Variations :** The process of handling different formats of URLs (30).
  - **Standardizing for Identity Consolidation :** Ensuring consistent URL formats to manage identities effectively (30).
- **User Information :**
  - **Resolving Screen Names :** Converting Twitter IDs to usernames (99).
  - **Twitter Usernames :** Identifiers for users on Twitter (11).
  - **User Object Example :** Representation of a Twitter user in JSON format (100).

## V

- **Vector Space Models** : Mathematical models used to represent text data in multidimensional space (217).
  - **3D Vector Example** : Visualization of vectors plotted in three-dimensional space (218).
  - **Vector Definition** : A quantity defined by both magnitude and direction (218).
- **Python Versions** : Various iterations of the Python programming language (1).
- **Views (CouchDB)** : Mechanisms for querying and retrieving data in CouchDB (53, 55).
- **Visualization Tools** : Tools used for creating visual representations of data (xvii).

## Visualizations

- **Constructing Friendship Graphs** : Techniques for visualizing friendships in Twitter data (108–117).
  - **Clique Detection** : Identifying and analyzing clusters of connected users (110–113).
  - **Infochimps Strong Links API** : A tool for visualizing strong relationships (114–116).
  - **Interactive 3D Graphs** : Visualization techniques for representing complex data (116).
- **Facebook Data Visualization** :
  - Various methods for visualizing Facebook connections (289).
  - **Mutual Friendships** : Visualizing friendships within groups (301–304).
  - **RGraphs** : A method for visualizing relationships in Facebook data (289–294).
  - **Spreadsheets** : Using spreadsheets for visualizing data (298).
  - **Sunburst Visualizations** : Techniques for representing hierarchical data (296).
  - **Rotating Tag Clouds** : Representing Facebook wall data as dynamic tag clouds (309–311).
- **Geographical Clustering** : Analyzing LinkedIn networks by geographical distribution (193–198).
  - **Dorling Cartograms** : Mapping networks using cartograms (198).
  - **Google Earth Mapping** : Visualizing networks in Google Earth (194–197).
- **Graph Your Inbox Chrome Extension** : A tool for visualizing email data (81).
- **Tweet Graphs** : Visual representation of tweet interactions (14–16).
  - **Visualizing Retweets** : Using Protovis for graphical representation (16).

## W

- **Wall Data (Facebook)** : Visualization of Facebook wall data as rotating tag clouds (309–311).
- **Web Page for This Book** : An online resource related to the book's content (xix).
- **Weighting Tags in Tag Clouds** : Techniques for adjusting the prominence of tags based on their importance (161).
- **WhitespaceTokenizer** : A tokenizer that splits text based on whitespace (248).
- **Wikipedia Articles with Geo Markup** : Articles containing geographical metadata (32).
- **Windows Systems** :
  - **ActivePython** : A Python distribution for Windows (1).
  - **Couchdb-lucene Service Wrapper** : A wrapper for using CouchDB with Lucene (64).
  - **DOT Language Output for Graphviz** : Format for visualizing graphs (165).
  - **GVedit Application** : A tool for editing Graphviz files (15).

- **Installing easy install** : Instructions for setting up Python package management (2).
- **WolframAlpha** : A computational knowledge engine used for entity analysis (258).
- **Word Tokenizer** : A tokenizer that splits text into words (248).
- **WP-Cumulus Tag Cloud** : A tag cloud implementation using WordPress (158, 309).

## X

- **XFN (XHTML Friends Network)** : A way to represent social connections in XHTML (20, 22–30).
  - **Example Markup** : Sample markup demonstrating XFN (22).
  - **Pseudocode for Breadth-First Search** : Algorithmic approach for crawling XFN links (24).
  - **Scraping XFN Content** : Techniques for extracting XFN data from web pages (23).
- **XHTML** : A markup language similar to HTML with stricter syntax (19).
- **Xoauth** : A protocol for OAuth authentication (232).
  - **xoauth.py Command-Line Utility** : A tool for managing OAuth processes (232).

## Z

- **Zipf's Law** : A principle describing the frequency distribution of words in a corpus (13).

These notes provide a simplified yet detailed overview of the specified content, highlighting important keywords and concepts for easier understanding.