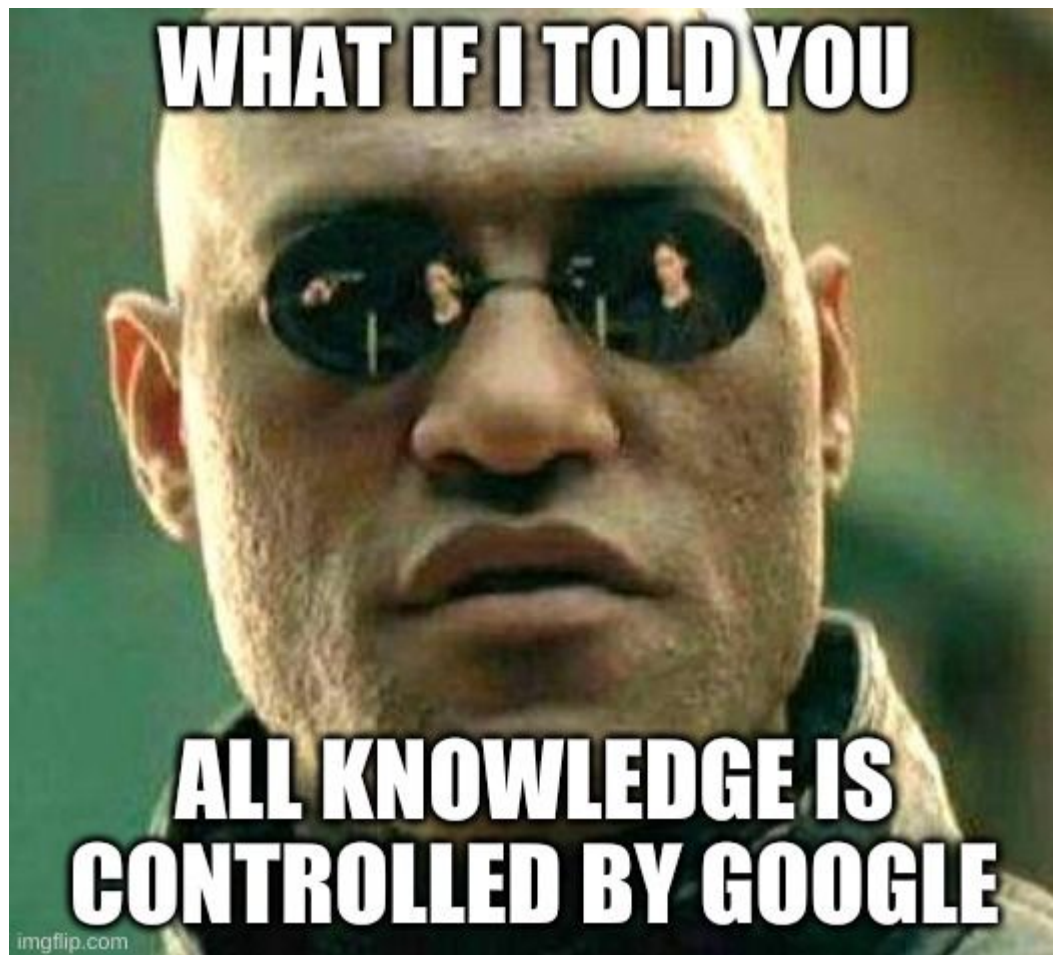


Creating a Knowledge Graph with Neo4j: A Simple Machine Learning Approach

Clair J. Sullivan, PhD
Data Science Advocate

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@CJLovesData1







**All materials for this demonstration are available on the
workshop GitHub repo:**

https://dev.neo4j.com/nodes2021_kg_workshop

Two different methods we can run today's code

1. Docker

- docker-compose build && docker-compose up
- Contains both Jupyter Lab and Neo4j database
- Not needed for today, but you will want access to Jupyter Lab somewhere

2. Neo4j Sandbox

- <https://dev.neo4j.com/sandbox>

We can either populate the database manually, or I will show how to download a pre-populated one...

THIS IS YOUR MACHINE LEARNING SYSTEM?

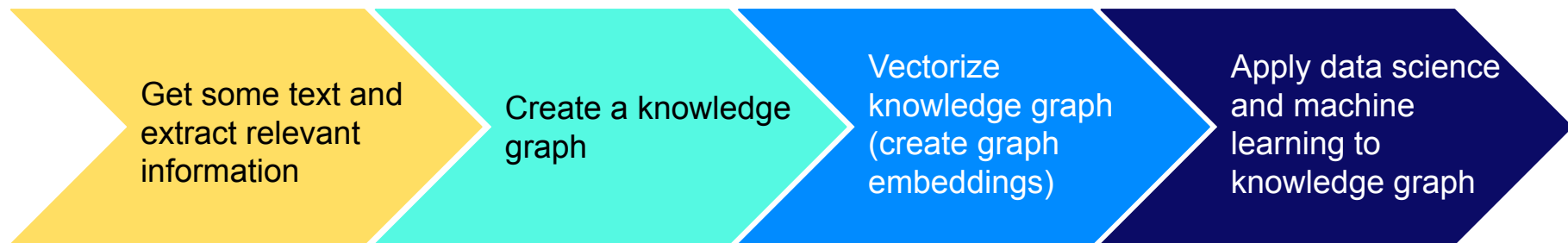
YUP! YOU POUR THE DATA INTO THIS BIG
PILE OF LINEAR ALGEBRA, THEN COLLECT
THE ANSWERS ON THE OTHER SIDE.

WHAT IF THE ANSWERS ARE WRONG?

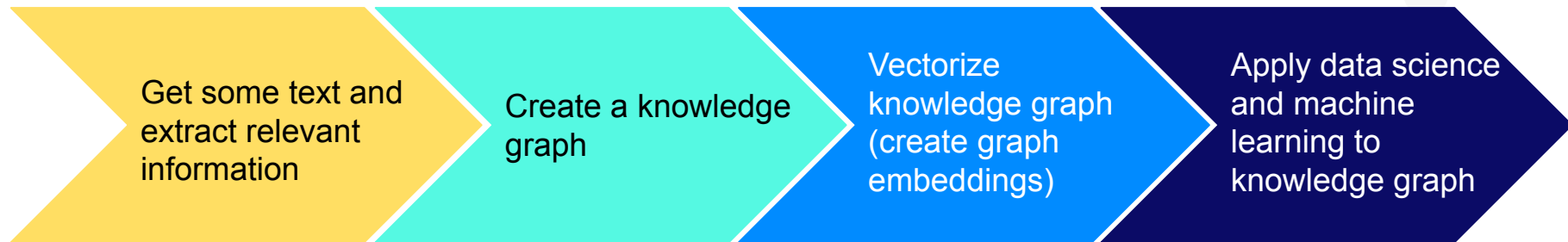
JUST STIR THE PILE UNTIL
THEY START LOOKING RIGHT.



By the end of this workshop you will be able to...



By the end of this workshop you will be able to...

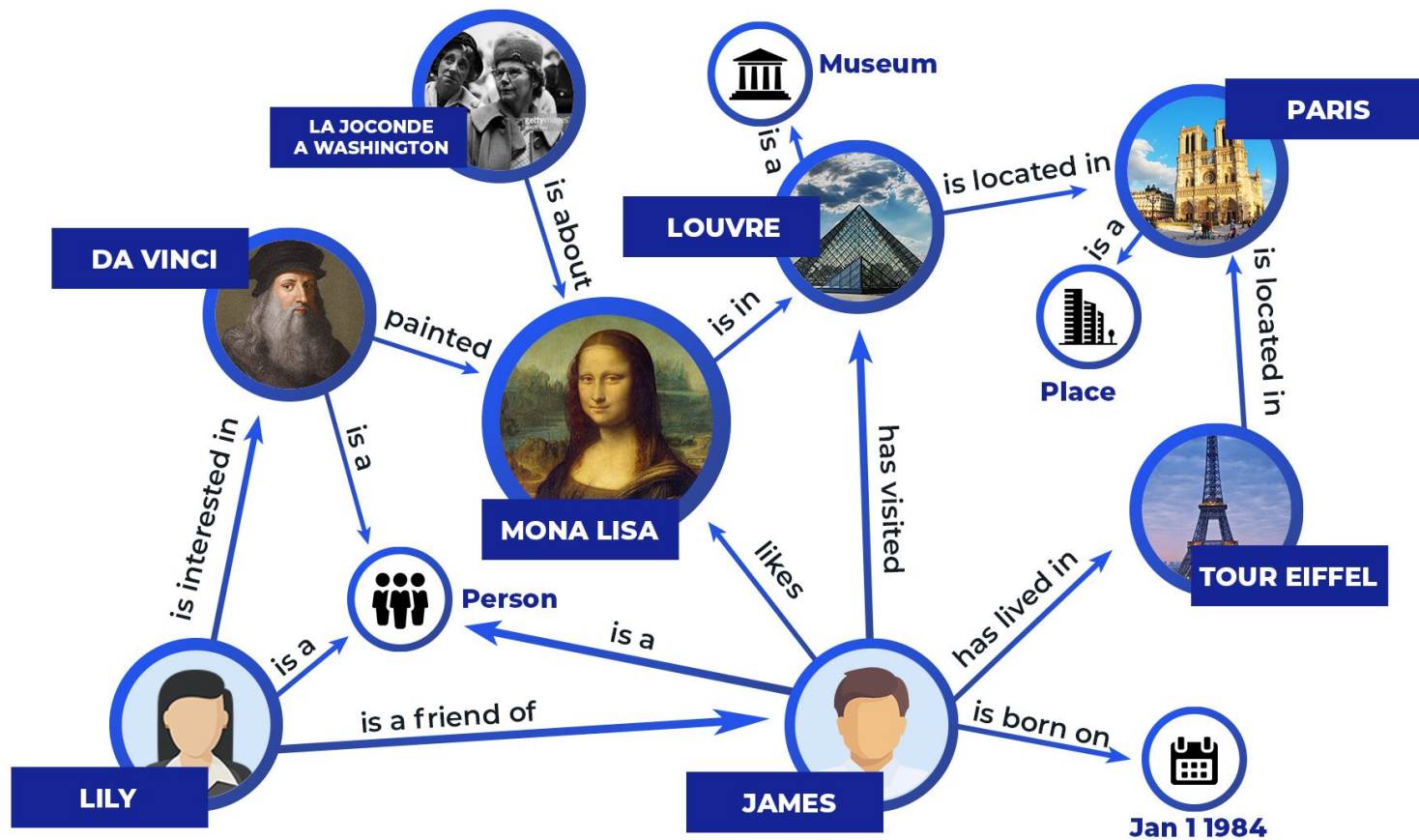


Natural Language Processing (NLP)

Graph Data Science Library + Basic ML

Two Key Concepts

1. There is no proverbial “silver bullet” with Natural Language Processing (NLP)
2. The quality of what you get out of a knowledge graph depends on the quality of what you put into it



<https://yashuseth.blog/2019/10/08/introduction-question-answering-knowledge-graphs-kgqa/>



Introduction to knowledge graphs

- “Things not strings”
- What knowledge graphs are useful for
 - Search
 - Question answering
 - Recommendation engine
- Can be generated a lot of different ways
 - Co-occurrence
 - Resource Description Framework (RDF)
 - Subject-Verb-Object (SVO)



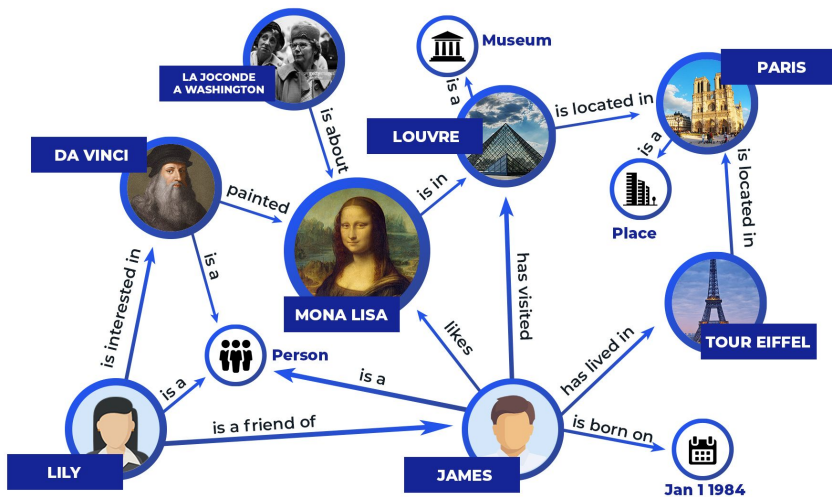
<https://covid19biblio.com/2020/04/28/keyword-co-occurrence-network-graph-for-the-overall-research-field-on-covid-19-up-to-april-27th-2020/>

RDF triples



https://en.wikipedia.org/wiki/Resource_Description_Framework#Examples

SVO triples



NLP considerations for knowledge graph creation

- Named Entity Recognition (NER)
- SVO / SPO triples
 - ...but verbs can be difficult to reliably detect via NLP!
- Very language dependent
- Very topic-area dependent

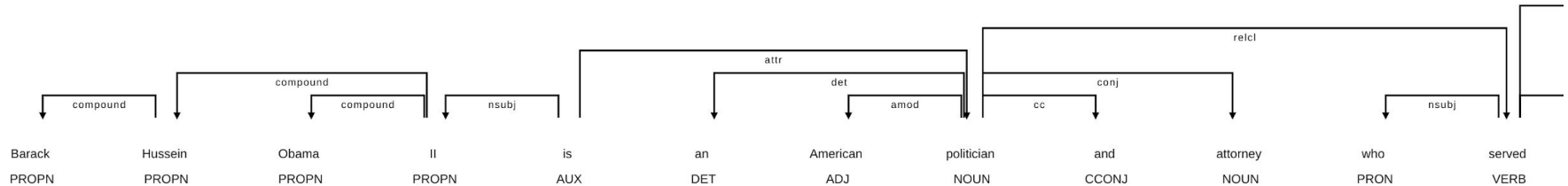
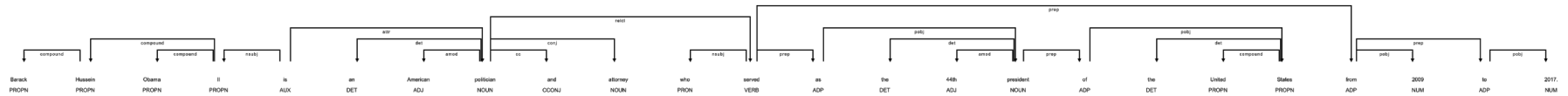
Barack Hussein Obama II **PERSON** ((listen) bə-RAHK hoo-SAYN oh-BAH-mə; born August 4, 1961 **DATE**) is an **American** **NORP** politician and attorney who served as the 44th **ORDINAL** president of the United States **GPE** from 2009 **DATE** to 2017 **DATE** . A member of the Democratic Party **ORG** , Obama **PERSON** was the first **ORDINAL** African-American **NORP** president of the United States **GPE** . He previously served as a U.S. **GPE** senator from Illinois **GPE** from 2005 to 2008 and as an Illinois **GPE** state senator from 1997 **DATE** to 2004.

Obama **PERSON** was born in Honolulu **GPE** , Hawaii **GPE** . After graduating from Columbia University **ORG** in 1983 **DATE** , he worked as a community organizer in Chicago **GPE** . In 1988 **DATE** , he enrolled in Harvard Law School **ORG** , where he was the first **ORDINAL** black person to be president of the Harvard Law Review **ORG** . After graduating, he became a civil rights attorney and an academic, teaching constitutional law at the University of Chicago Law School **ORG** from 1992 **DATE** to 2004. Turning to elective politics, he represented the 13th **ORDINAL** district from 1997 **DATE** until 2004 **DATE** in the Illinois Senate, when he ran for the U.S. Senate **ORG** . Obama **PERSON** received national attention in 2004 **DATE** with his March Senate **ORG** primary win, his well-received July **DATE** Democratic National Convention keynote address, and his landslide November **DATE** election to the Senate **ORG** . In 2008 **DATE** , he was nominated by the Democratic Party **ORG** for president a year **DATE** after beginning his campaign, and after a close primary campaign against Hillary Clinton **PERSON** . Obama **PERSON** was elected over Republican **NORP** Senator John McCain **PERSON** in the general election and was inaugurated alongside his running mate, Joe Biden **PERSON** , on January 20, 2009 **DATE** . Nine months later **DATE** , he was named the 2009 **DATE** Nobel Peace Prize **WORK_OF_ART** laureate.

Obama **PERSON** signed many landmark bills into law during his first two years **DATE** in office. The main reforms that were passed include the Affordable Care Act **LAW** (commonly referred to as ACA **ORG** or " Obamacare **WORK_OF_ART** "), although without a public health insurance option, the Dodd–Frank Wall Street Reform and Consumer Protection Act, and the Don't Ask, Don't Tell Repeal Act of 2010 **DATE** . The American Recovery and Reinvestment Act **ORG** of 2009 **DATE** and Tax Relief, Unemployment Insurance Reauthorization, and Job Creation Act of 2010 **DATE** served as economic stimuli amidst the Great Recession **EVENT** . After a lengthy debate over the national debt limit, he signed the Budget Control **ORG** and the American Taxpayer Relief Acts **ORG** . In foreign policy, he increased U.S. **GPE** troop levels in Afghanistan **GPE** , reduced nuclear weapons with the United States– Russia New START treaty, and ended military involvement in the Iraq War **EVENT** . He ordered military involvement in Libya **GPE** for the implementation of the UN Security Council **ORG** Resolution 1973 **DATE** , contributing to the overthrow of Muammar Gaddafi **PERSON** . He also ordered the military operations that resulted in the deaths of Osama bin Laden **PERSON** and suspected American **NORP** Al-Qaeda **ORG** operative Anwar al-Awlaki **PERSON** .

After winning re-election by defeating Republican **NORP** opponent Mitt Romney **PERSON** , Obama **PERSON** was sworn in for a second **ORDINAL** term in 2013 **DATE** . During this term, he promoted inclusion for LGBT Americans **NORP** . His administration filed briefs that urged the Supreme Court **ORG** to strike down same-sex marriage bans as unconstitutional (United States **GPE** v. Windsor **PERSON** and Obergefell **ORG** v. Hodges **PERSON**); same-sex marriage was legalized nationwide in 2015 **DATE** after the Court **ORG** ruled so in Obergefell **ORG** . He advocated for gun control in response to the Sandy Hook Elementary School **ORG** shooting, indicating support for a ban on assault weapons, and issued wide-ranging executive actions concerning global warming and immigration. In foreign policy, he ordered military intervention in Iraq **GPE** in response to gains made by ISIL **ORG** after the 2011 **DATE** withdrawal from Iraq **GPE** , continued the process of ending U.S. **GPE** combat operations in Afghanistan **GPE** in 2016 **DATE** , promoted discussions that led to the 2015 **DATE** Paris Agreement **EVENT** on global climate change, initiated sanctions against Russia **GPE** following the invasion in Ukraine **GPE** and again after interference in the 2016 **DATE** U.S. **GPE** elections, brokered the JCPOA **ORG** nuclear deal with Iran **GPE** , and normalized U.S. **GPE** relations with Cuba **GPE** . Obama **PERSON** nominated three **CARDINAL** justices to the Supreme Court **ORG** : Sonia Sotomayor **PERSON** and Elena Kagan **PERSON** were confirmed as justices, while Merrick Garland **PERSON** faced partisan obstruction from the Republican **NORP** -led Senate **ORG** led by Mitch McConnell **PERSON** , which never held hearings or a vote on the nomination. Obama **PERSON** left office in January 2017 **DATE** and continues to reside in Washington **GPE** , D.C. During Obama's **PERSON** term in office, the United States' **GPE** reputation abroad, as well as the American **NORP** economy, significantly improved. Obama **PERSON** 's presidency has generally been regarded favorably, and evaluations of his presidency among historians, political scientists, and the general public frequently place him among the upper tier of American **NORP** presidents.

Barack Hussein Obama II is an American politician and attorney who served as the 44th president of the United States from 2009 to 2017.



Barack Hussein Obama II is an American politician and attorney who served as the 44th president of the United States from 2009 to 2017.

Text	Lemma	Tag	POS	DEP	is_stop
Barack	Barack	NNP	PROPN	compound	FALSE
Hussein	Hussein	NNP	PROPN	compound	FALSE
Obama	Obama	NNP	PROPN	compound	FALSE
II	II	NNP	PROPN	nsubj	FALSE
is	be	VBZ	AUX	ROOT	TRUE
an	an	DT	DET	det	TRUE
American	american	JJ	ADJ	amod	FALSE
politician	politician	NN	NOUN	attr	FALSE
and	and	CC	CCONJ	cc	TRUE
attorney	attorney	NN	NOUN	conj	FALSE
who	who	WP	PRON	nsubj	TRUE
served	serve	VBD	VERB	relcl	FALSE
as	as	IN	ADP	prep	TRUE
the	the	DT	DET	det	TRUE
44th	44th	JJ	ADJ	amod	FALSE
president	president	NN	NOUN	pobj	FALSE
of	of	IN	ADP	prep	TRUE
the	the	DT	DET	det	TRUE
United	United	NNP	PROPN	compound	FALSE
States	States	NNP	PROPN	pobj	FALSE
from	from	IN	ADP	prep	TRUE
2009	2009	CD	NUM	pobj	FALSE
to	to	IN	ADP	prep	TRUE
2017	2017	CD	NUM	pobj	FALSE
.	.	.	PUNCT	punct	FALSE

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States	States	NNP	PROPN	pobj	FALSE
from	from	IN	ADP	prep	TRUE
2009	2009	CD	NUM	pobj	FALSE
to	to	IN	ADP	prep	TRUE
2017	2017	CD	NUM	pobj	FALSE
.	.	.	PUNCT	punct	FALSE

An introduction to the tools we will use today

- spacy
- Wikipedia Python package
- Google Knowledge Graph
- Pywikibot
- Neo4j
 - Awesome Procedures on Cypher (APOC)
 - Graph Data Science (GDS) Library
 - Cypher

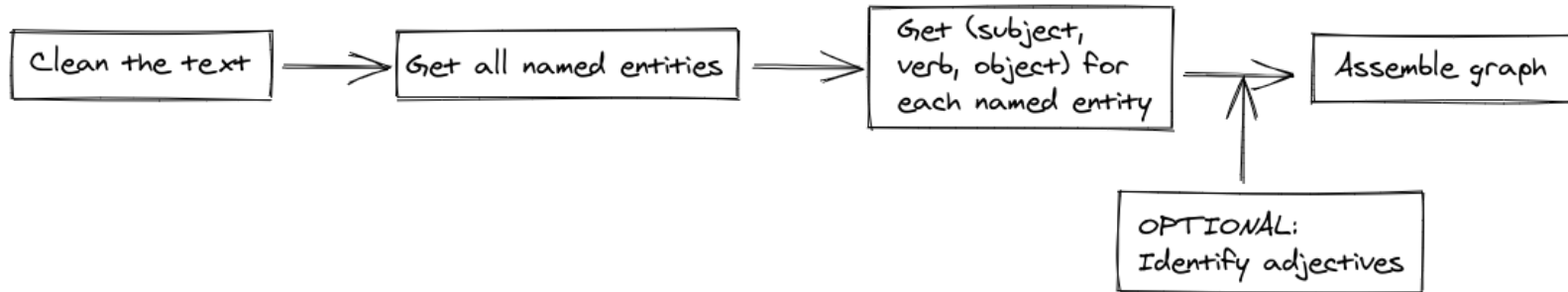


Clone the GitHub repository at
https://dev.neo4j.com/nodes2021_kg_workshop

Method 1: The NLP Only Approach



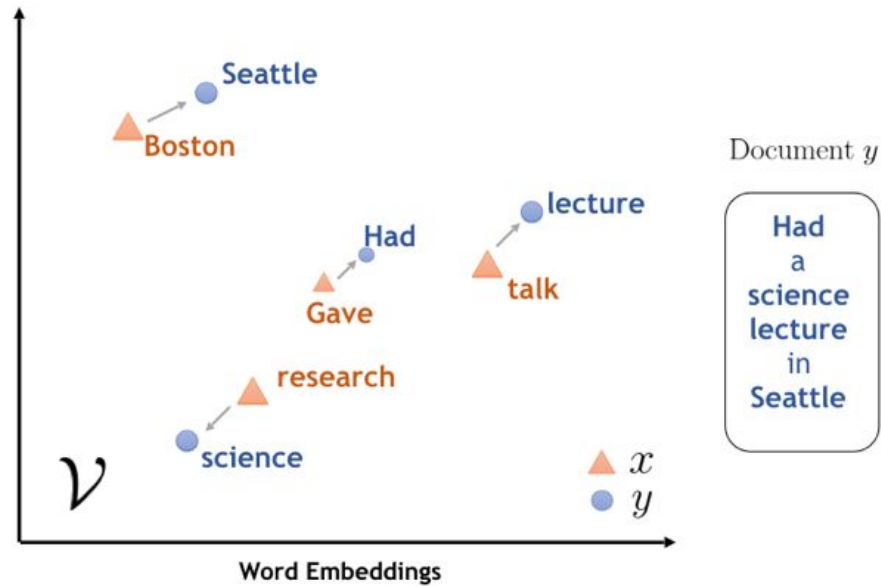
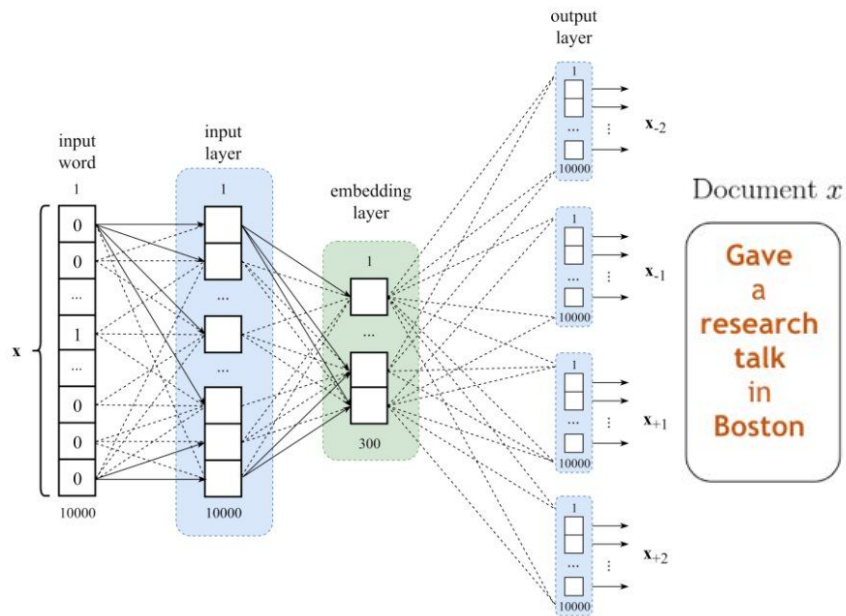
Some ways we could get this done: NLP only approach



Advantage: limitless verbs

Drawback: entity disambiguation

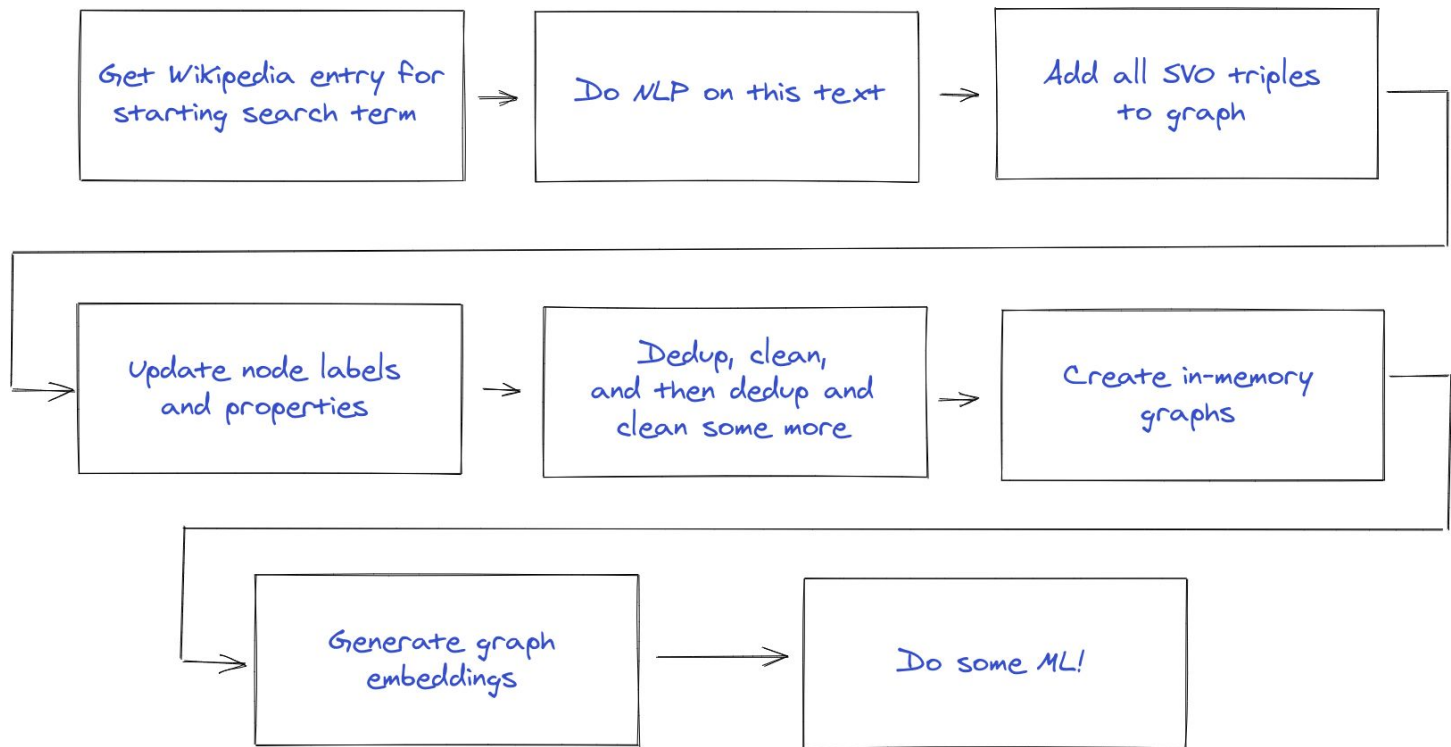
word2vec



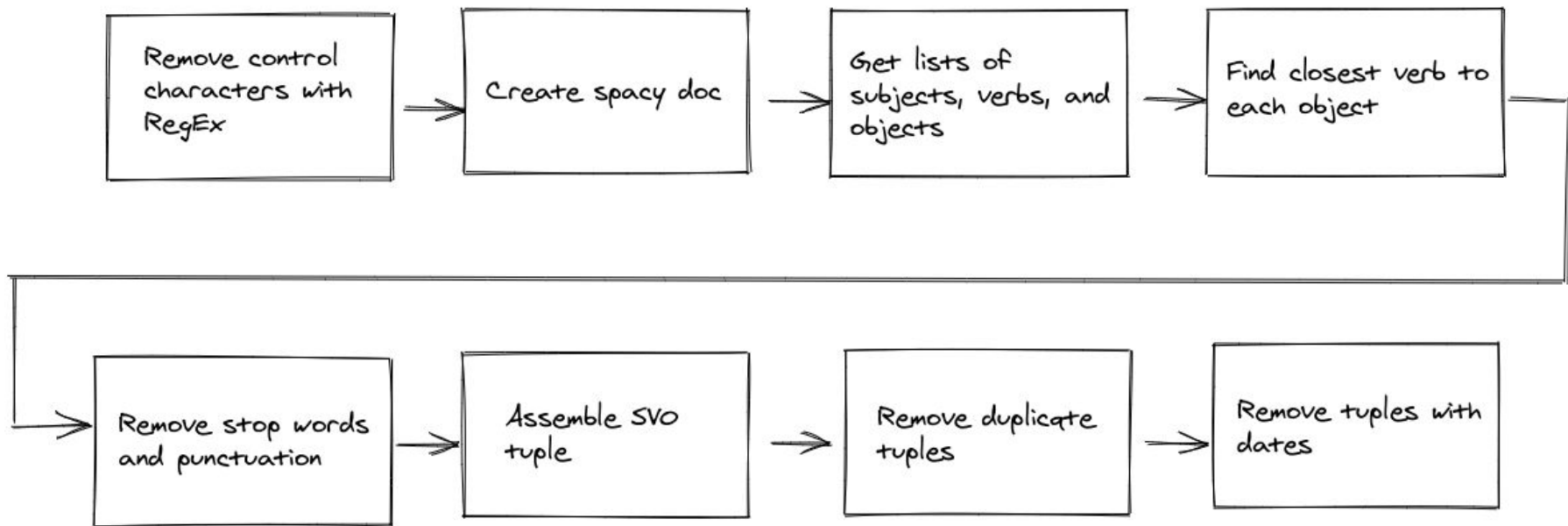
<https://www.kdnuggets.com/2019/01/burkov-self-supervised-learning-word-embeddings.html>

<https://medium.com/swlh/word2vec-in-practice-for-natural-language-processing-a179b3286a21>

Overview of workflow




NLP workflow



Create a Google Knowledge API key

<https://developers.google.com/knowledge-graph/how-tos/authorizing>

Home > Search Central > Knowledge Graph Search API

Rate and review  

Authorize Requests

When your application requests public data, the request doesn't need to be authorized, but does need to be accompanied by an identifier, such as an API key.

Your application needs to identify itself every time it sends a request to the Google Knowledge Graph Search API, by including an [API key](#) with each request.

Acquiring and using an API key

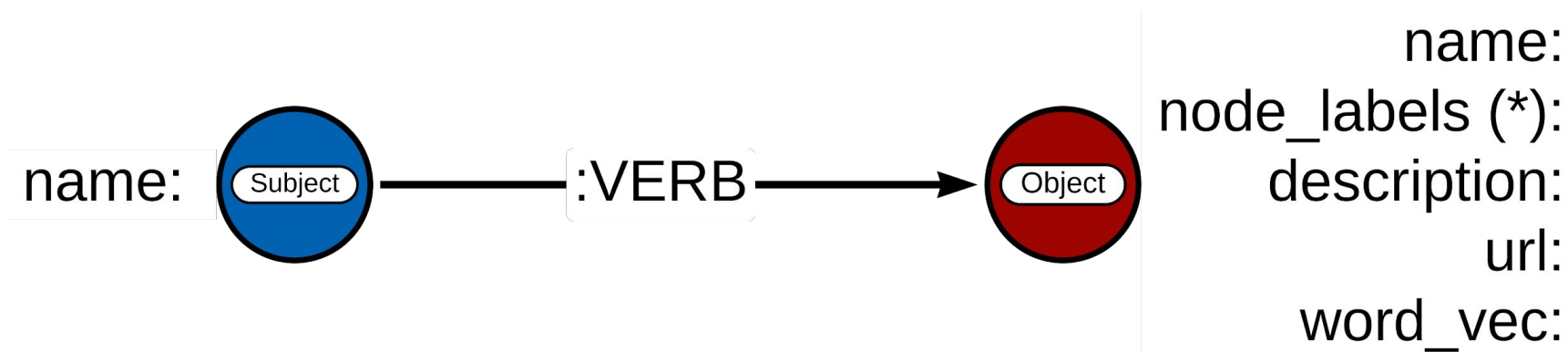
To acquire an API key:

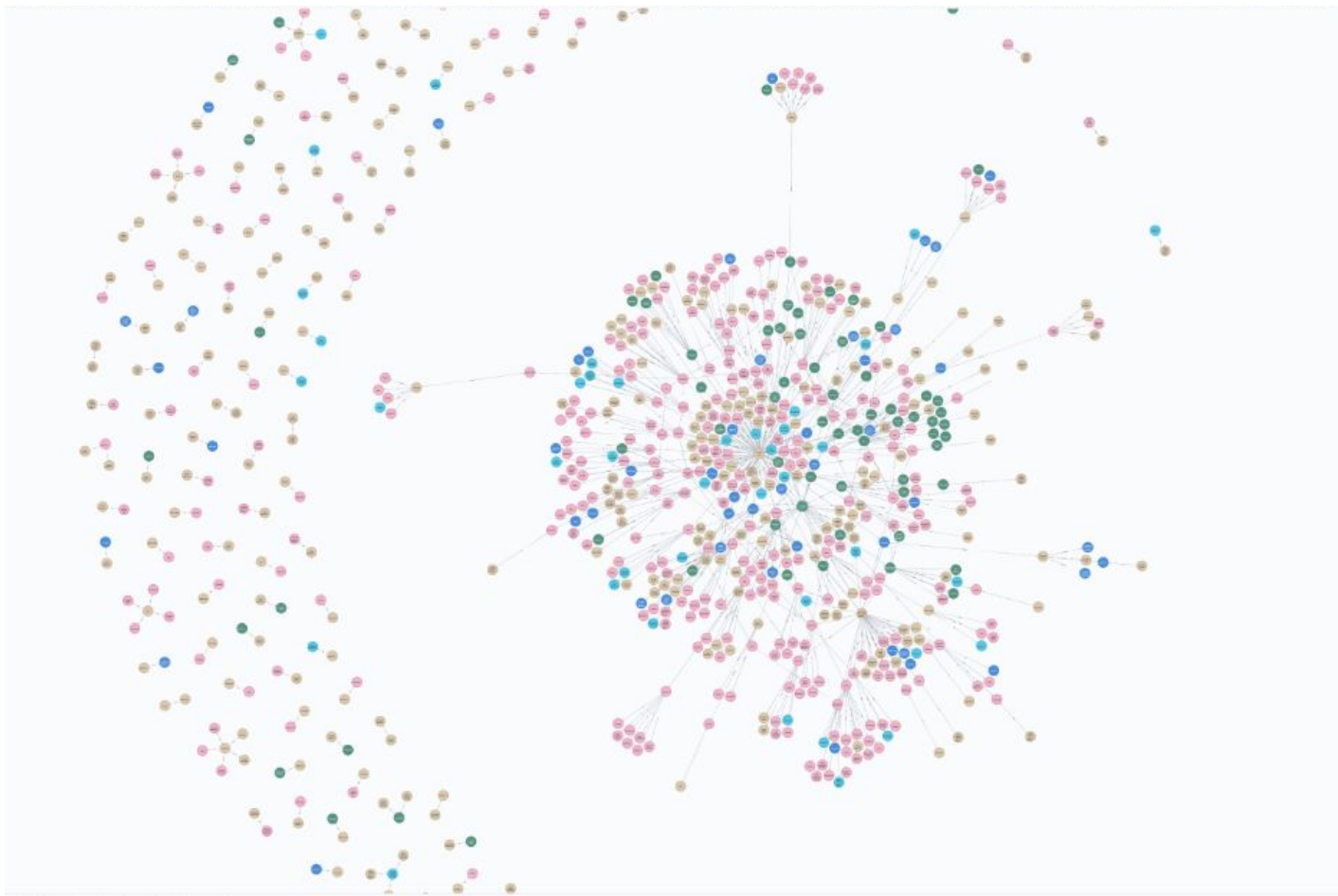
1. Open the [Credentials page](#) in the API Console.
2. This API supports two types of credentials. Create whichever credentials are appropriate for your project:

Enhance the existing data with Google Knowledge Graph

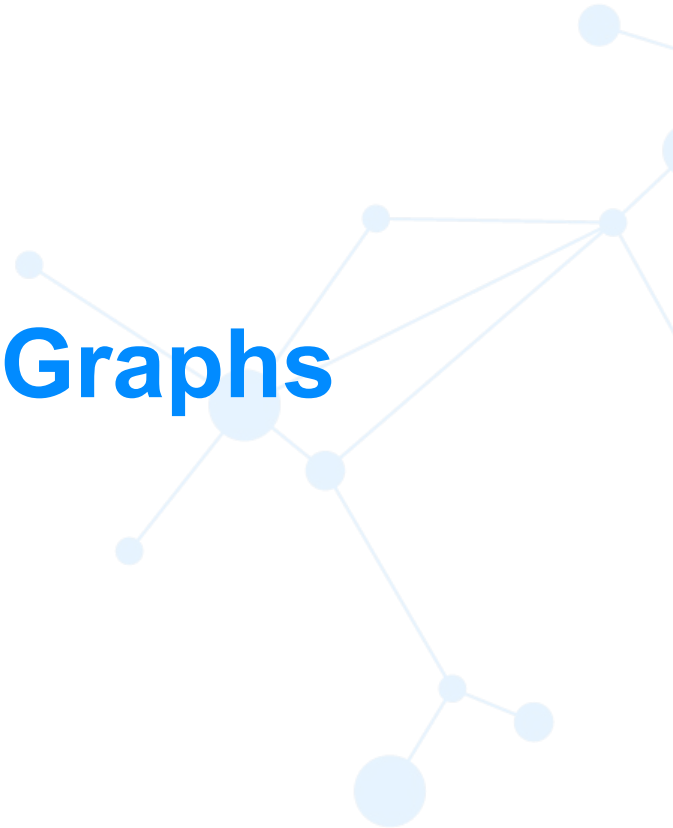
```
{...
  "@type": "ItemList",
  "itemListElement": [
    {
      "@type": "EntitySearchResult",
      "result": {
        "@id": "kg:/m/0dl567",
        "name": "Taylor Swift",
        "@type": [
          "Thing",
          "Person"
        ],
      },
    },
  ],
  ...
  "detailedDescription": {
    "articleBody": "Taylor Alison Swift is an American singer-songwriter and actress. Raised in Wyomissing, Pennsylvania, she moved to Nashville, Tennessee, at the age of 14 to pursue a career in country music. ",
    "url": "http://en.wikipedia.org/wiki/Taylor_Swift",
  },
  ...
}
```

Detailed knowledge graph data model





Machine Learning on Graphs



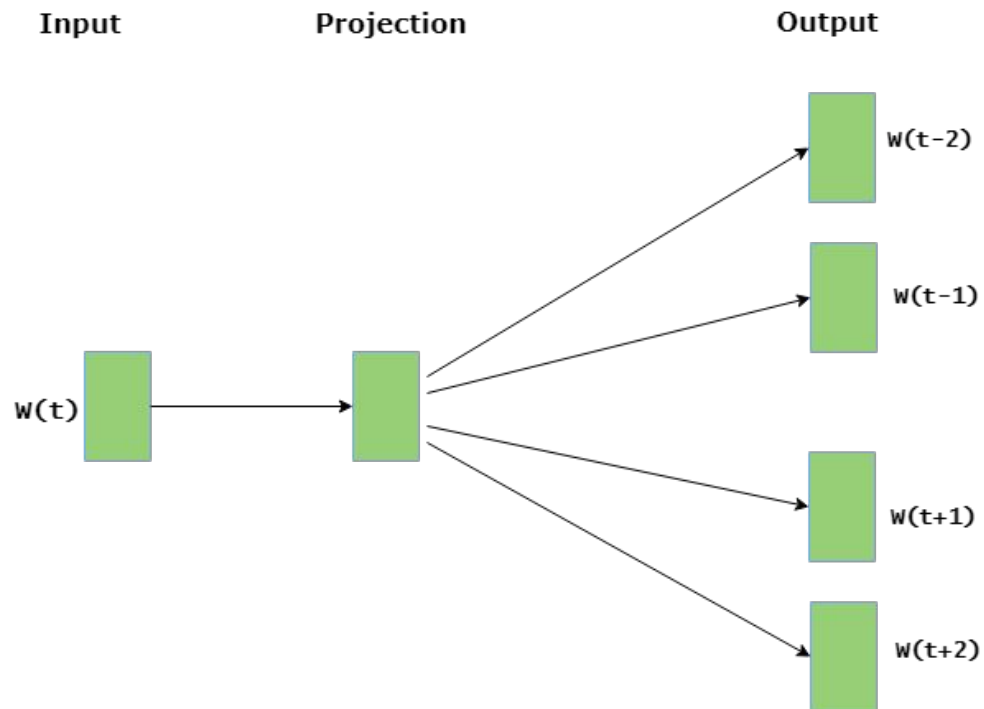
Why machine learning with (knowledge) graphs?

- Traditional ML uses a relational database-type model
 - All data points are independent of each other
 - Example: churn prediction based on user behavior
- Graphs (and graph databases) treat relationships as a “first class citizen”
 - Models can include homophily
 - Example: churn prediction includes the churn of neighbors within the graph
 - Models can also include the same data as the traditional, independent data point models

Example: making a better recommendation engine

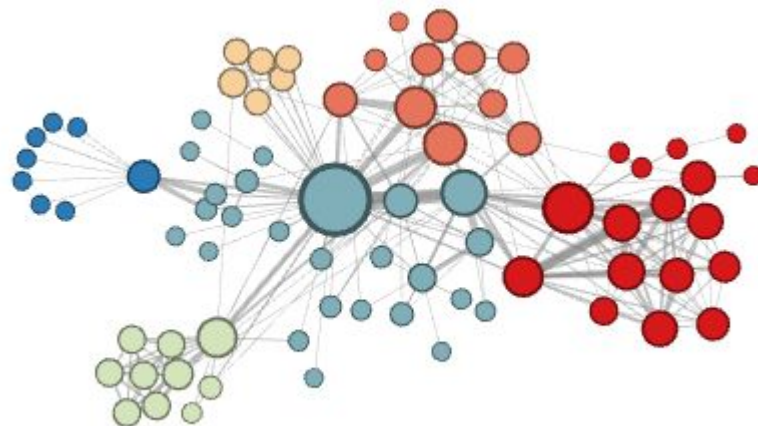
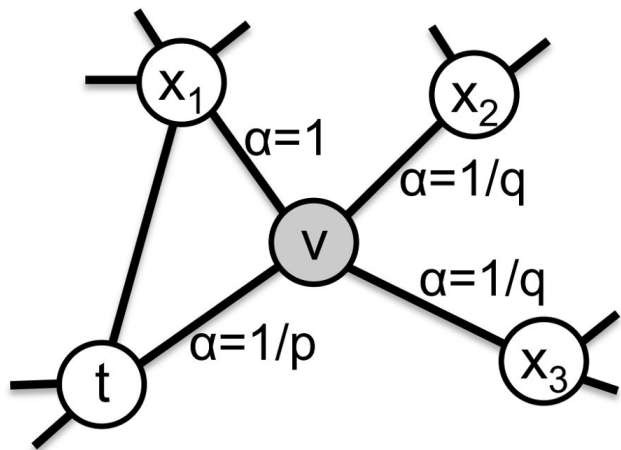


word2vec



Note: word2vec typically creates one vector per word. The spacy implementation of vectorization takes a document (sentence) and averages the word vectors across the sentence.

node2vec



node2vec



	name	embedding
1	"Barack Obama"	[-0.5534299612045288, 0.319044291973114, -0.06302239000797272, 0.8757740259170532, -0.5034562945365906, 0.23735041916370392, 0.15117834508419037, 0.8566229939460754, 0.36209946870803833, -0.6797583103179932]
2	"United States of America"	[0.1451471447944641, 0.4807624816894531, 0.4366985261440277, 0.42269086837768555, 0.20110560953617096, -0.5779915452003479, -0.10465864837169647, -0.04139380902051926, 0.3290615975856781, -0.495746374130249]
3	"Democratic Party"	[0.19489407539367676, 0.5242791771888733, -0.7722358703613281, 0.15843135118484497, -0.5232059955596924, 0.5803580284118652, 0.17970407009124756, -0.6052649617195129, -0.7680787444114685, 0.5753467679023743]
4	"Illinois"	[0.8053464293479919, 0.2300983965396881, 0.7079187035560608, -0.03613480180501938, 0.4691833555698395, -0.38967591524124146, 0.0824178084731102, -0.27919191122055054, 0.23097757995128632, 0.7676025032997131]
5	"Honolulu"	[0.5645546317100525, -0.8217434287071228, 0.5297825336456299, 0.31918787956237793, -0.4469479024410248, 0.8200243711471558, -0.4185393154621124, -0.3348398506641388, -0.5732030272483826, -0.39435911178588867]
6	"Hawaii"	[-0.5108500719070435, 0.12454281747341156, 0.2569912075996399, -0.6748168468475342, 0.24597491323947906, 0.5893328189849854, 0.26128533482551575, -0.7081990838050842, -0.5841189622879028, 0.13823509216308594]

Embedding dimension: 10

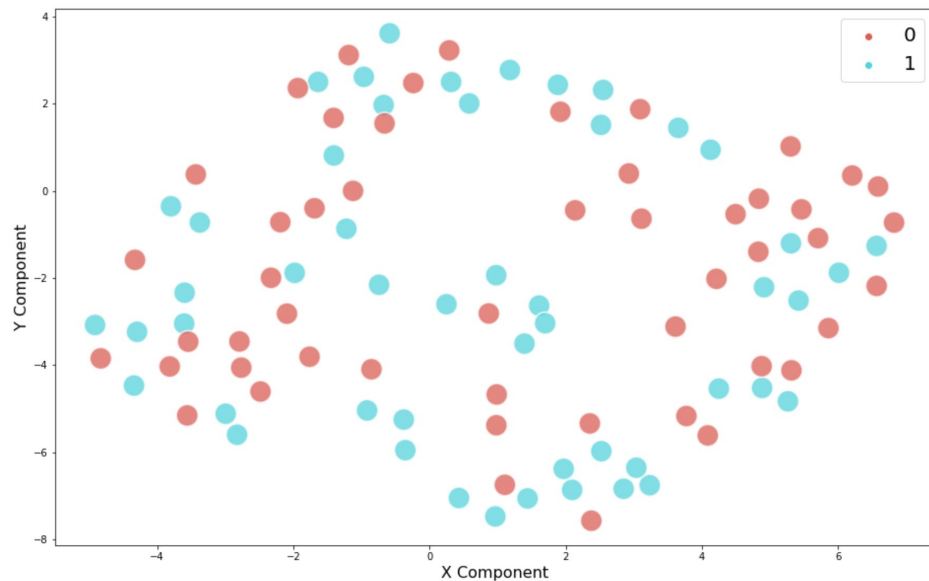
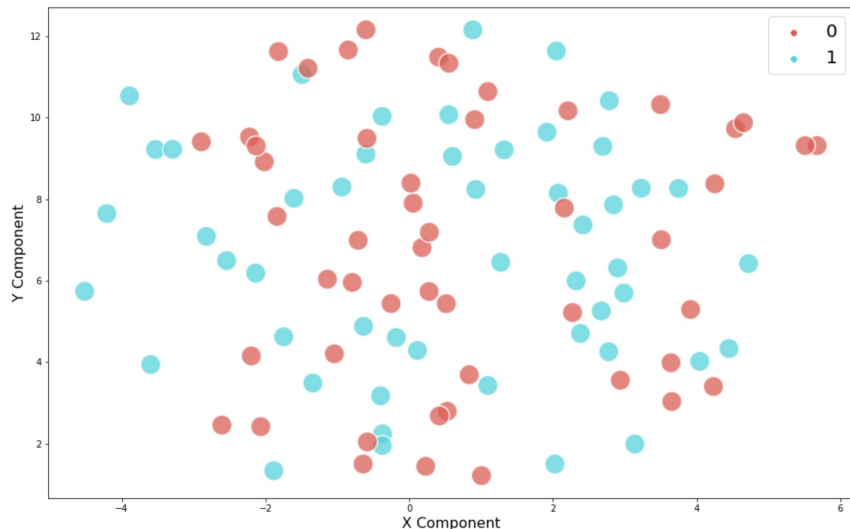
Node similarity via embeddings



	u.name	n.name	n.type_ls	similarity
1	"mixed-sex education"	"Columbia University"	["private university"]	0.13848771879851898
2	"capital"	"Washington, D.C."	["capital"]	0.1296056718640691
3	"landlocked country"	"Afghanistan"	["sovereign state"]	0.11288100303291404
4	"big city"	"Chicago"	["city of the United States"]	0.08881633377710593
5	"social state"	"Ukraine"	["sovereign state"]	0.08480072967702501

Embedding dimension: 300

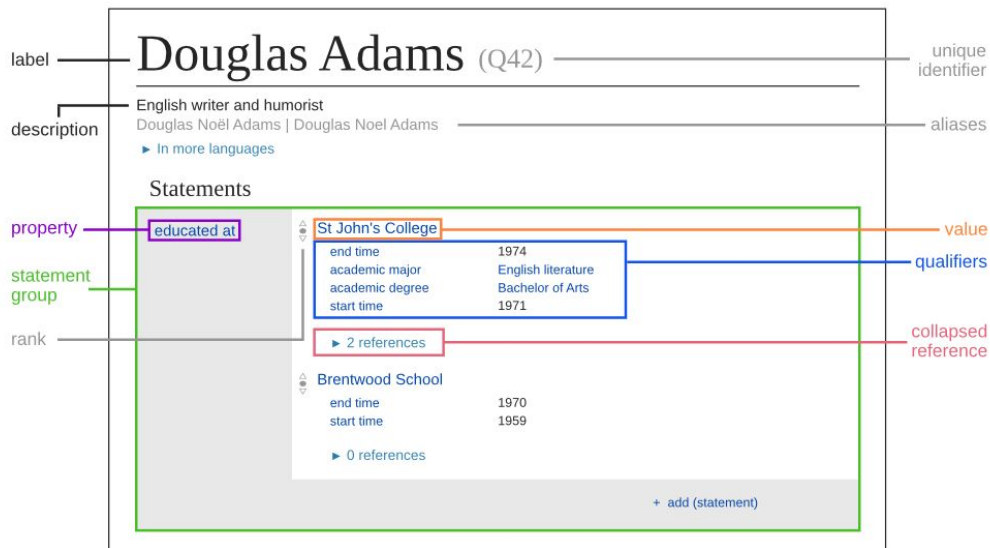
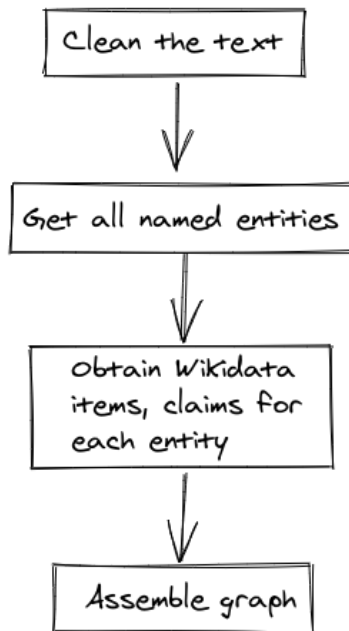
Visualizing embeddings with t-SNE



Method 2: The NLP Lite Approach



Some ways we could get this done: NLP “lite”



Advantage: entity disambiguation

Drawback: must specify which verbs you are interested in

Create a PyWikiBot token

<https://heardlibrary.github.io/digital-scholarship/host/wikidata/bot/>


[Home](#) > [Host](#) > [Wikidata](#) > [bot](#)

Building A Bot to Interact with Wikidata or Wikibase
[Preliminaries](#)
[Set up the bot](#)

Use the bot to write to the Wikidata test instance
[Background](#)
[Running bot](#)
[Modifying the script](#)
[Making edits to the real Wikidata](#)

Adding data to a Wikibase instance
[Preliminaries](#)
[Running the bot](#)
[Some notes on the load_csv.py script](#)

Building A Bot to Interact with Wikidata or Wikibase



Preliminaries

What is a bot?

The term “bot” conjures up an image of a cool robot that can do your bidding. Unfortunately, a bot is not a robot. It is a computer program that can communicate with Wikidata or Wikibase using the [Transfer Protocol \(HTTP\)](#). The program can be written in any language that can communicate with a web server.

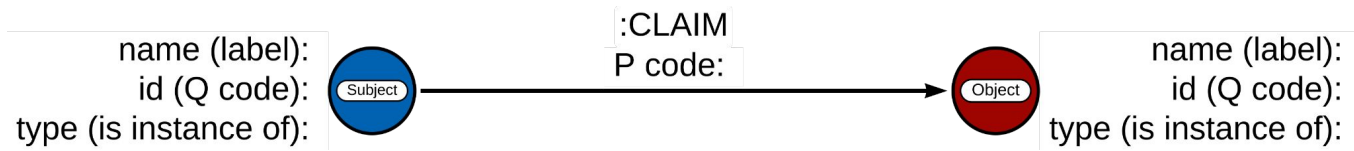
What is the difference between Wikidata and Wikibase?

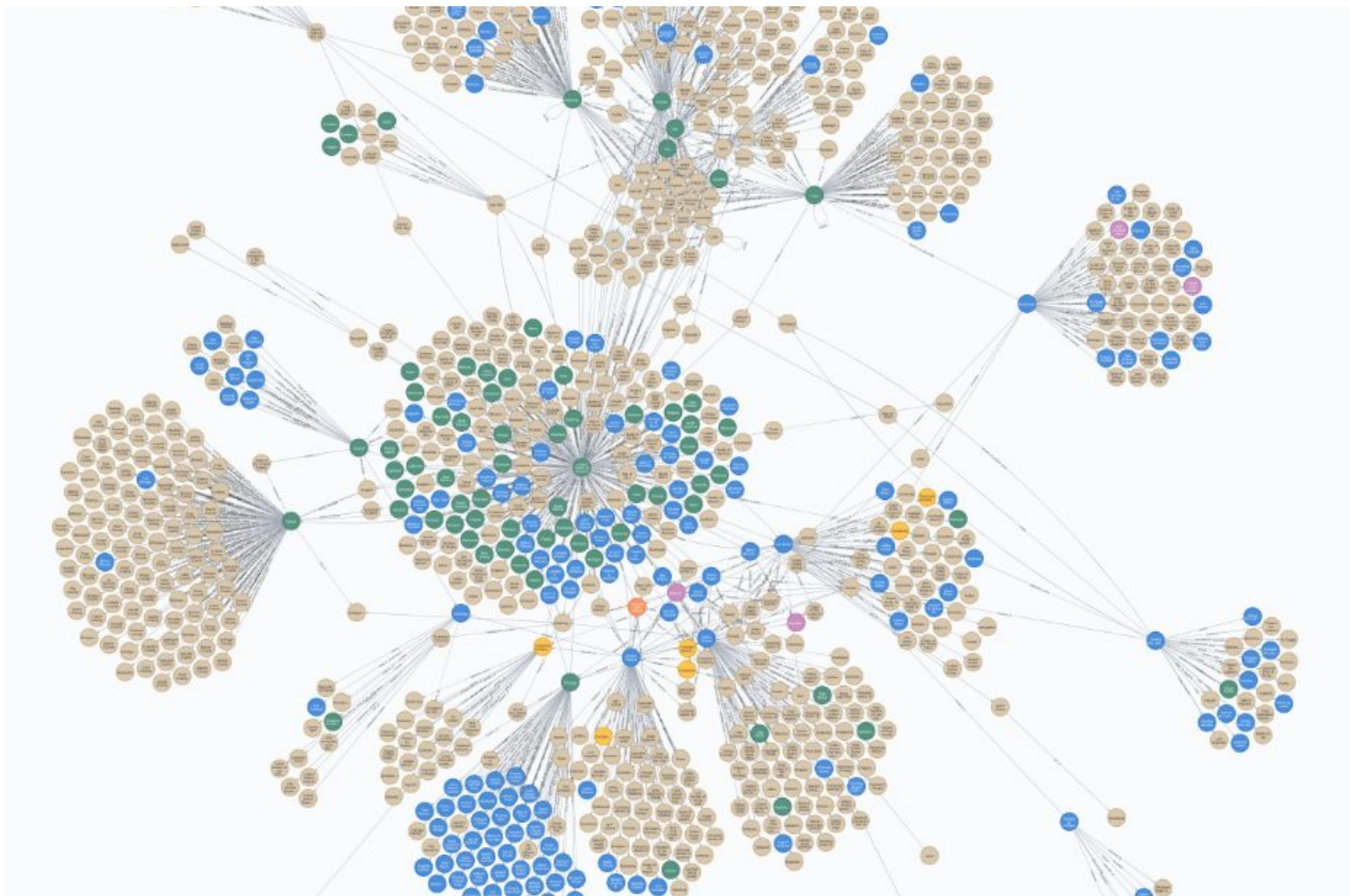
[Wikidata](#) is a giant database and knowledge graph that anyone can edit. It is an underpinned by manual edits in Wikidata, but data can also be edited via a bot. Because it would be risky to test your bot's code there without danger of damaging anything real. We will use the test instance of Wikidata.

[Wikibase](#) is the underlying software application upon which [Wikidata](#) is built. Wikibase is used to test tools and data structures that might eventually find their way to Wikidata.

Wikibase can be [set up on your local computer](#) and accessed using a `localhost:` address.

Because Wikibase is so empty, it would take a lot of work to enter any meaningful amount of data. Unfortunately, [Quickstatements](#), one of the most useful tools for populating Wikidata with data, is not available on Wikibase. Wikibase users are likely to be interested in entering data into it using a bot.





Where to go from here?

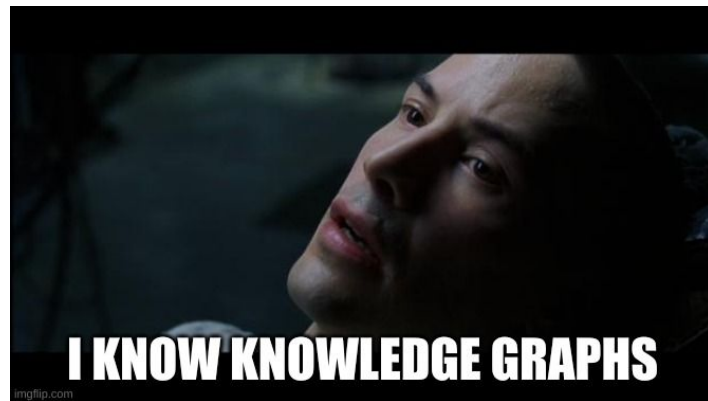


Two Key Concepts

1. There is no proverbial “silver bullet” with Natural Language Processing (NLP)
2. The quality of what you get out of a knowledge graph depends on the quality of what you put into it

What could we do from here?

- Add nodes to the graph!
- Various embedding optimization techniques
- Add data for creating embeddings
 - Ex: Word vectors from text descriptions
- Different embedding/modeling techniques
 - FastRP
 - GraphSAGE
 - GNN





Problems we could solve

- Community/cluster detection
- Node classification, link prediction
- Graph-to-graph classification
 - Useful for comparing two different knowledge graphs
- Unstructured text, NLP
- Question answering systems

Thank you!

clair.sullivan@neo4j.com
@CJLovesData1

