Advanced Data Visualization Lecture Notes (Lecture 7 - 2 Hours)

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1. Heatmap

Definition:

A heatmap is a data visualization technique that shows the magnitude of a phenomenon as color in two dimensions. The values are represented using color gradients, making it easy to spot patterns and correlations in a dataset.

Use Cases:

- Visualizing correlation matrices.
- Highlighting missing data.
- Monitoring website user activity (click maps).
- Representing geospatial data.

Applications:

- Financial sector: Correlation between different stocks.
- Healthcare: Patient data analysis.
- Marketing: Website heatmaps to improve user experience.

Python Implementation:
python
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```
import seaborn as sns
import matplotlib.pyplot as plt

# Sample correlation matrix heatmap
data = sns.load_dataset('penguins').dropna()
correlation = data.corr()

sns.heatmap(correlation, annot=True, cmap='coolwarm')
plt.show()
```

FAQ:

- **What does a darker color represent?** Darker colors typically indicate a higher intensity or stronger correlation.

- **How is a heatmap different from a scatter plot?** A heatmap shows aggregated data with colors, while a scatter plot shows individual data points.

Theory (Simple Explanation):

A heatmap helps visualize relationships between different variables using colors. For example, in a dataset of penguins, you can see how flipper length correlates with body mass by observing the color strength between these two variables.

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2. Word Cloud

Definition:

A word cloud is a visual representation of text data where the size of each word represents its frequency or importance in the dataset.

Use Cases:

- Summarizing text documents.
- Analyzing customer reviews.
- Exploring common themes in social media posts.

Applications:

- Marketing: Extracting key topics from customer feedback.
- Journalism: Highlighting important terms in speeches or news articles.
- Research: Summarizing scientific papers.

Here's a step-by-step guide to apply each of these methods (biplot, PCA, t-SNE, word cloud, POS tagging) and generate word clouds for nouns, adjectives, and verbs only.

5. POS Tagging and Creating Word Clouds for Nouns, Adjectives, Verbs Only

Steps:

1. **Collect the Text Data**: Load a document, paragraph, or sentence(s) that you want to analyze.
2. **Tokenize the Text**: Split the text into individual words using a tokenizer.
3. **Apply POS Tagging**: Use `nltk.pos_tag()` to label each word with its part of speech.
4. **Filter POS Tags**: Select only the words that are tagged as nouns (NN), adjectives (JJ), and verbs (VB).

5. **Create the Word Cloud**: Generate a word cloud using only these filtered words.

Summary of Steps for Word Cloud Creation from POS Tags:

1. Tokenize the text into individual words.
2. Use POS tagging to label each word with its part of speech.
3. Filter out nouns, adjectives, and verbs from the tagged words.
4. Create a word cloud from the filtered words using the WordCloud library.

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1. Biplot (with PCA)

Steps:

1. **Collect the Data**: Start with a dataset that has multiple variables (e.g., `Iris`, `Penguins`, or your custom dataset).
2. **Normalize the Data**: If necessary, standardize the data (mean = 0, variance = 1) to make sure all variables are on the same scale.
3. **Apply PCA**: Use the `PCA` function from the `sklearn` library to reduce the data dimensions to two (PC1 and PC2).
4. **Plot the Biplot**:
    - Create a scatter plot of the data points in the reduced dimension.
    - Draw arrows representing the original variables' contribution to the principal components.
    - Label the axes (Principal Component 1, Principal Component 2) and add the variable names.

Python Code Example:

python

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```
# (Refer to the biplot example code provided earlier)
```

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2. PCA (Principal Component Analysis)

Steps:

1. **Collect the Data**: Gather the dataset with many features.
2. **Standardize the Data**: Scale the data if the variables are on different scales.
3. **Apply PCA**: Use `sklearn.decomposition.PCA` to reduce the dimensions, choosing how many components you want to retain (e.g., 2 components).
4. **Visualize the Data**: Plot the reduced data in a 2D scatter plot or a biplot to interpret how the variables contribute to the main components.

Python Code Example:

python

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```
from sklearn.decomposition import PCA

from sklearn.datasets import load_iris

import matplotlib.pyplot as plt


# Load dataset

iris = load_iris()

X = iris.data


# Apply PCA

pca = PCA(n_components=2)

X_pca = pca.fit_transform(X)


# Plot the PCA result

plt.scatter(X_pca[:, 0], X_pca[:, 1], c=iris.target)

plt.xlabel('Principal Component 1')

plt.ylabel('Principal Component 2')
```

```
plt.show()
```

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3. t-SNE (t-Distributed Stochastic Neighbor Embedding)

Steps:

1. **Collect the Data**: Gather the dataset with multiple dimensions (e.g., images, text embeddings).
2. **Apply t-SNE**: Use the `TSNE` function from `sklearn.manifold` to reduce the dataset to two or three dimensions.
3. **Visualize the Data**: Plot the reduced data to observe clusters or groupings in the dataset.

Python Code Example:

python

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```
from sklearn.manifold import TSNE

from sklearn.datasets import load_digits

import matplotlib.pyplot as plt


# Load dataset

digits = load_digits()

X = digits.data

y = digits.target


# Apply t-SNE

tsne = TSNE(n_components=2, random_state=0)
```

```
X_tsne = tsne.fit_transform(X)


# Plot the result

plt.scatter(X_tsne[:, 0], X_tsne[:, 1], c=y)

plt.colorbar()

plt.show()
```

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4. Word Cloud

Steps:

1. **Collect the Text Data**: Use any text data (e.g., customer reviews, articles, or a text corpus).
2. **Preprocess the Text**: Clean the text by removing unnecessary characters, stopwords, and punctuation.
3. **Generate a Word Cloud**: Use the `WordCloud` class from the `wordcloud` library to create a visual representation of the text data, where more frequent words appear larger.

Python Implementation:

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```
from wordcloud import WordCloud
import matplotlib.pyplot as plt

text = "Machine learning is a field of artificial intelligence that
uses statistical techniques to give computer systems the ability to
learn from data."

wordcloud = WordCloud(width=800, height=400,
background_color='white').generate(text)
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
```

```
plt.show()
```

FAQ:

- **Can I create a word cloud from a CSV file?** Yes, you can extract text data from any source, including CSV files, and generate a word cloud.
- **Does word frequency always determine word size?** In most cases, yes, but you can customize the algorithm to prioritize other factors.

Theory (Simple Explanation):

A word cloud emphasizes the most frequent words in a block of text by increasing their size. It's a simple way to see what words are being mentioned the most in a document or group of comments.

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3. POS Tagging

Definition:

Part-of-Speech (POS) tagging is the process of labeling each word in a sentence with its grammatical role, such as noun, verb, adjective, etc.

Use Cases:

- Natural language processing (NLP) for understanding text.
- Machine translation.
- Text-to-speech systems.

Applications:

- Sentiment analysis.
- Chatbots and virtual assistants.
- Language translation.

Python Implementation:
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```
import nltk
from nltk import word_tokenize, pos_tag

sentence = "Artificial intelligence is transforming the world."
tokens = word_tokenize(sentence)
```

```
pos_tags = pos_tag(tokens)

print(pos_tags)
```

FAQ:

- **How many POS tags are there?** There are around 36 standard POS tags used in English (e.g., NN for noun, VB for verb).
- **Why is POS tagging important for NLP?** It helps machines understand the grammatical structure and meaning of sentences.

Theory (Simple Explanation):

POS tagging breaks down sentences into individual words and labels each word based on its role in the sentence. For example, in the sentence "AI is evolving," "AI" is a noun and "evolving" is a verb.

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4. PCA (Principal Component Analysis)

Definition:

Principal Component Analysis (PCA) is a dimensionality reduction technique that transforms a large set of variables into a smaller one that still contains most of the information.

Use Cases:

- Reducing the number of variables in machine learning models.
- Data visualization in 2D or 3D.
- Noise reduction in data.

Applications:

- Image compression.
- Stock market analysis.
- Genetics and biology.

2. PCA (Principal Component Analysis)

Steps:

1. **Collect the Data**: Gather the dataset with many features.
2. **Standardize the Data**: Scale the data if the variables are on different scales.

3. **Apply PCA**: Use `sklearn.decomposition.PCA` to reduce the dimensions, choosing how many components you want to retain (e.g., 2 components).
4. **Visualize the Data**: Plot the reduced data in a 2D scatter plot or a biplot to interpret how the variables contribute to the main components.

Python Implementation:

python
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```
from sklearn.decomposition import PCA
from sklearn.datasets import load_iris
import matplotlib.pyplot as plt

# Load dataset
data = load_iris()
X = data.data

# Apply PCA
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)

# Plot the PCA result
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=data.target)
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.show()
```

FAQ:

- **Why use PCA?** It helps reduce the complexity of datasets while preserving as much information as possible.
- **What are principal components?** They are new variables created by combining existing variables in a way that captures the maximum variance.

Theory (Simple Explanation):

PCA simplifies datasets by transforming them into a smaller set of variables while retaining the essential patterns. It's like compressing a file without losing important information.

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5. t-SNE (t-Distributed Stochastic Neighbor Embedding)

Definition:

t-SNE is a dimensionality reduction technique that is particularly good for visualizing high-dimensional data in two or three dimensions.

Use Cases:

- Visualizing clusters in high-dimensional data.
- Exploring relationships in word embeddings.
- Understanding the structure of neural network activations.

Applications:

- Image recognition.
- Genomics.
- NLP embeddings.

3. t-SNE (t-Distributed Stochastic Neighbor Embedding)

Steps:

1. **Collect the Data**: Gather the dataset with multiple dimensions (e.g., images, text embeddings).
2. **Apply t-SNE**: Use the `TSNE` function from `sklearn.manifold` to reduce the dataset to two or three dimensions.
3. **Visualize the Data**: Plot the reduced data to observe clusters or groupings in the dataset.

Python Implementation:
python
Copy code

```
from sklearn.manifold import TSNE
from sklearn.datasets import load_digits
import matplotlib.pyplot as plt

# Load dataset
digits = load_digits()
X = digits.data
```

```
y = digits.target

# Apply t-SNE
tsne = TSNE(n_components=2, random_state=0)
X_tsne = tsne.fit_transform(X)

# Plot the result
plt.scatter(X_tsne[:, 0], X_tsne[:, 1], c=y)
plt.colorbar()
plt.show()
```

FAQ:

- **How does t-SNE differ from PCA?** t-SNE is more focused on preserving the local structure of the data, while PCA preserves the global structure.
- **Why is t-SNE useful for visualizing data?** It does a good job of grouping similar points together, making it easier to spot clusters.

Theory (Simple Explanation):

t-SNE takes data with many features and squashes it into two or three dimensions. It's great for understanding relationships in complex datasets, such as seeing clusters of similar data points.

Definition:

A biplot is a type of plot that simultaneously displays both the data points and the relationships between variables in a dataset. It is a combination of a scatter plot for the data points and vectors (arrows) that represent the original variables. This makes it particularly useful in the context of dimensionality reduction techniques such as PCA.

Use Cases:

- Visualizing the relationships between variables in a multivariate dataset.
- Understanding the principal components in PCA and how variables contribute to these components.
- Identifying patterns in high-dimensional datasets.

Applications:

- Exploratory data analysis in research.
- Identifying the most influential variables in machine learning.
- Interpreting results of PCA or other dimensionality reduction techniques.

Python Implementation:

python
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```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.decomposition import PCA
from sklearn.datasets import load_iris

# Load dataset
iris = load_iris()
X = iris.data
y = iris.target
labels = iris.feature_names

# Apply PCA
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)

# Create a biplot
def biplot(X_pca, pca, labels):
    plt.figure(figsize=(8, 6))

    # Scatter plot of data points
    plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='viridis')
    plt.xlabel('PC1')
    plt.ylabel('PC2')

    # Plot arrows for each feature (loading vectors)
    for i, label in enumerate(labels):
        plt.arrow(0, 0, pca.components_[0, i], pca.components_[1, i],
color='r', alpha=0.5)
        plt.text(pca.components_[0, i] * 1.2, pca.components_[1, i] *
1.2, label, color='g', ha='center', va='center')

    plt.show()

biplot(X_pca, pca, labels)
```

1. Biplot (with PCA)

Steps:

1. **Collect the Data**: Start with a dataset that has multiple variables (e.g., `Iris`, `Penguins`, or your custom dataset).
2. **Normalize the Data**: If necessary, standardize the data (mean = 0, variance = 1) to make sure all variables are on the same scale.
3. **Apply PCA**: Use the `PCA` function from the `sklearn` library to reduce the data dimensions to two (PC1 and PC2).
4. **Plot the Biplot**:
    - Create a scatter plot of the data points in the reduced dimension.
    - Draw arrows representing the original variables' contribution to the principal components.
    - Label the axes (Principal Component 1, Principal Component 2) and add the variable names.

FAQ:

- **What is the difference between a biplot and a scatter plot?** A scatter plot shows just the data points, while a biplot also shows the original variables as vectors or arrows.
- **Why use a biplot with PCA?** A biplot helps you interpret which original variables (arrows) contribute the most to the principal components (axes) and how the data points relate to these variables.

Theory (Simple Explanation):

A biplot helps you visualize both your data points and the underlying structure of your variables. For example, when applying PCA, it shows how the original variables contribute to the newly created dimensions (principal components) and how the data points relate to these dimensions. It gives a clear picture of both the relationships between the data points and the influence of each variable.

Interpreting a Biplot

A **biplot** displays two types of information at the same time:

1. **Data points** (the individual observations in the dataset).
2. **Variables** (the original features or variables in the dataset, represented by vectors/arrows).

When interpreting a biplot, the goal is to understand how the data points are distributed in the new reduced-dimensional space (typically from PCA) and how the original variables influence that distribution.

Here's a step-by-step guide on how to interpret a biplot:

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1. Data Points (Dots or Circles)

- **Position**: Each dot represents an observation (data point) projected onto the principal components (PC1 and PC2).
    - Observations that are **closer to each other** are more similar in terms of the variables.
    - Observations that are **further apart** are more different from each other.
- **Clusters**: If you see groups of points that are clustered together, it indicates that these observations share common characteristics or are more related to each other based on the variables.

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2. Variables (Vectors or Arrows)

- **Length of Arrows**:
    - Longer arrows indicate that the corresponding variable has a **stronger influence** on the principal components.
    - Shorter arrows suggest that the variable contributes less to explaining the variation in the data.
- **Direction of Arrows**:
    - The direction of the arrow indicates how that variable relates to the principal components.
    - For example, if an arrow points in the direction of a particular cluster of points, this variable is important in explaining why those observations are grouped together.
- **Angle Between Arrows**:
    - Arrows that are **close to each other (small angle)** suggest that the corresponding variables are **positively correlated**.
    - Arrows at **90 degrees** to each other suggest that the variables are **uncorrelated**.
    - Arrows that point in **opposite directions** (large angle, close to 180 degrees) indicate a **negative correlation** between the variables.

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3. Relationship Between Data Points and Variables

- **Projection of Points onto Arrows**:
    - The position of the data points relative to the arrows gives information about how much each variable contributes to that observation.
    - If a data point is **close to the tip of an arrow**, that observation has a high value for the corresponding variable.
    - If a data point is **perpendicular** to an arrow or far from it, the variable has a low or no influence on that observation.
- **Importance of Variables**:
    - The direction of each arrow shows which variables influence the principal components the most. For example, if an arrow points to the right (PC1 axis), that variable is more important for PC1.
    - Observations near the arrow direction are strongly influenced by the corresponding variable.

Example: Interpreting a PCA Biplot

Step-by-Step Interpretation:

1. **Principal Components**: Look at the axes labeled as PC1 and PC2. These are the new variables (principal components) created by PCA. PC1 explains the most variance, and PC2 explains the second most.
2. **Data Points**: Each point on the plot is an observation from the dataset. Points that are close together are similar in the space defined by the principal components, and those far apart are more dissimilar.
3. **Arrows for Variables**:
    - If one arrow (variable) is longer, that variable has a significant influence on the data points along the principal component axis. For example, if an arrow points along the PC1 axis, it means this variable explains a lot of the variation in PC1.
    - If two arrows point in the same direction, the corresponding variables are positively correlated. For example, if two variables have arrows pointing in the same direction and there are many points along this direction, it shows these variables are positively associated with those data points.
    - If arrows are perpendicular, it means the variables they represent are uncorrelated.
4. **Observations & Variables**:
    - Check which data points are in the direction of which arrows. If a data point lies close to an arrow, it means that particular variable has a strong influence on that data point.
    - If a cluster of data points lies in the direction of a variable's arrow, those observations share high values for that variable.

Key Takeaways:

- **Data Points (Dots)**: Similarity of observations.
- **Arrows (Variables)**: Strength and direction of the influence of each variable.
- **Correlation of Variables**: Direction and angle between arrows help interpret relationships between variables (correlated, uncorrelated, negatively correlated).

Visual Example

If you have a **biplot** where:

- **PC1** explains 60% of the variance.
- **PC2** explains 30% of the variance.
- Variables like **Flipper Length** and **Body Mass** have long arrows pointing in similar directions.

You can infer that **Flipper Length** and **Body Mass** are strongly correlated and influence how the data is spread along the PC1 axis. Observations that are far in the direction of these arrows likely have high values for both of these variables.