ench-nouns-gender-analysis-exp1-v1

February 12, 2025

1 French Noun Gender Classification in Word Embeddings: SHAP & LIME Analysis on a Perceptron Model

1.1 Install gdown

[ ]:
```
!pip install gdown
```

```
Requirement already satisfied: gdown in /usr/local/lib/python3.11/dist-packages
(5.2.0)
Requirement already satisfied: beautifulsoup4 in /usr/local/lib/python3.11/dist-
packages (from gdown) (4.13.3)
Requirement already satisfied: filelock in /usr/local/lib/python3.11/dist-
packages (from gdown) (3.17.0)
Requirement already satisfied: requests[socks] in
/usr/local/lib/python3.11/dist-packages (from gdown) (2.32.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.11/dist-packages
(from gdown) (4.67.1)
Requirement already satisfied: soupsieve>1.2 in /usr/local/lib/python3.11/dist-
packages (from beautifulsoup4->gdown) (2.6)
Requirement already satisfied: typing-extensions>=4.0.0 in
/usr/local/lib/python3.11/dist-packages (from beautifulsoup4->gdown) (4.12.2)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.11/dist-packages (from requests[socks]->gdown) (3.4.1)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-
packages (from requests[socks]->gdown) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.11/dist-packages (from requests[socks]->gdown) (2.3.0)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.11/dist-packages (from requests[socks]->gdown)
(2025.1.31)
Requirement already satisfied: PySocks!=1.5.7,>=1.5.6 in
/usr/local/lib/python3.11/dist-packages (from requests[socks]->gdown) (1.7.1)
```

1.2 Download Camem-BERT Embeddings with Noun Genders

- Camem-BERT Embeddings with French Noun Genders
- https://drive.google.com/file/d/1u39fPDJYqPHmZSdPflzn3zXtBKZjx9vY/view?usp=sharing

[ ]:
```python
import gdown

file_id = "1u39fPDJYqPHmZSdPflzn3zXtBKZjx9vY"  # Extracted from link
output = "camem_bert_embeddings_with_noun_gender.csv"  # File name
gdown.download(f"https://drive.google.com/uc?id={file_id}", output, quiet=False)
```

```
Downloading…
From (original):
https://drive.google.com/uc?id=1u39fPDJYqPHmZSdPflzn3zXtBKZjx9vY
From (redirected): https://drive.google.com/uc?id=1u39fPDJYqPHmZSdPflzn3zXtBKZjx
9vY&confirm=t&uuid=d1bdedd1-a800-4946-a555-f5d5a017531d
To: /content/my_file.csv
100%|      | 2.72G/2.72G [00:43<00:00, 62.4MB/s]
```

[ ]: 'my_file.csv'

1.3 Dataset Head

[ ]:
```python
import pandas as pd

# Display the head of the DataFrame
df = pd.read_csv("camem_bert_embeddings_with_noun_gender.csv")

display(df.head())
```

	Word	Embedding	Gender
0	a b c	[-0.03363805636763573,0.18951943516731262,-0.0…	1
1	a demi-mot	[-0.06961638480424881,0.11719649285078049,0.00…	1
2	a-mi-la	[-0.055688682943582535,0.05570295825600624,-0…	1
3	aabam	[0.01503327488899231,0.16362543404102325,0.026…	1
4	aalénien	[-0.07107880711555481,0.05070320889353752,-0.0…	1

Check the length of the embeddings

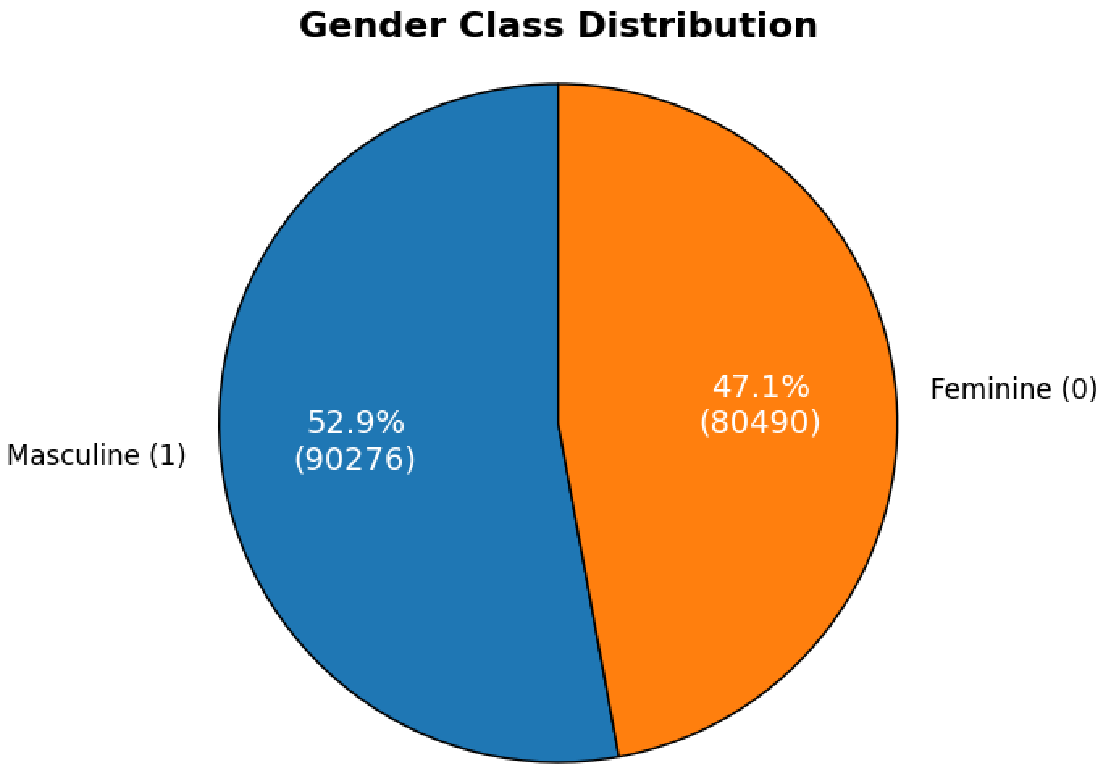
[ ]:
```python
# Extract the first embedding and check its length
embedding_length = len(eval(df['Embedding'].iloc[0]))

print(f"Embedding Length: {embedding_length} dimensions")
```

```
Embedding Length: 768 dimensions
```

1.4 Dataset Exploration

[ ]:
```python
import matplotlib.pyplot as plt

# Ensure the dataset is loaded and mapped correctly
gender_labels = {1: "Masculine (1)", 0: "Feminine (0)"}
df['Gender_Label'] = df['Gender'].map(gender_labels)
```

```python
# Calculate gender distribution
gender_counts = df['Gender_Label'].value_counts()

# Function to format labels with count and percentage
def label_format(pct, all_vals):
    absolute = int(round(pct/100. * sum(all_vals)))  # Calculate absolute count
    return f"{pct:.1f}%\n({absolute})"  # Display percentage and count

# Create the pie chart
plt.figure(figsize=(8, 6))
wedges, texts, autotexts = plt.pie(
    gender_counts,
    labels=gender_counts.index,
    autopct=lambda pct: label_format(pct, gender_counts),  # Apply formatting␣
 ↪function
    startangle=90,
    wedgeprops={'edgecolor': 'black'},  # Improve visibility
    textprops={'fontsize': 12}  # Set font size
)

# Improve text visibility
for text in autotexts:
    text.set_color('white')
    text.set_fontsize(14)

plt.title('Gender Class Distribution', fontsize=16, fontweight='bold')
plt.axis('equal')  # Equal aspect ratio to ensure a circular pie chart

# Show the pie chart
plt.show()
```



[ ]:
```
# Display 10 examples for each gender
examples_per_gender = df.groupby('Gender').head(10)

# Display the table
from IPython.display import display
display(examples_per_gender)
```

```
                Word                                          Embedding  \
0              a b c  [-0.03363805636763573,0.18951943516731262,-0.0…
1         a demi-mot  [-0.06961638480424881,0.11719649285078049,0.00…
2           a-mi-la  [-0.055688682943582535,0.05570295825600624,-0…
3              aabam  [0.01503327488899231,0.16362543404102325,0.026…
4           aalénien  [-0.07107880711555481,0.05070320889353752,-0.0…
5          aaléniens  [-0.02594040334224701,0.07717090100049973,-0.0…
6                aba  [-0.009327867068350315,0.27434393763542175,0.0…
7              abaca  [-0.05669710785150528,0.3120356500148773,-0.06…
8             abacas  [-0.053496845066547394,0.2737475335597992,-0.1…
9            abacule  [-0.029825951904058456,0.0692121610045433,-0.1…
13            abadie  [-0.04138301685452461,0.12789814174175262,0.07…
14           abadies  [-0.032471708953380585,0.14253003895282745,-0…
15           abaisse  [-0.028545105829834938,0.04448898509144783,-0…
16          abaisses  [-0.021061692386865616,0.14140108227729797,-0…
```

```
23         abaissée  [0.02088659629225731,0.059765733778476715,-0.0…
24        abaissées  [-0.05247421935200691,0.15887975692749023,-0.0…
25          abajoue  [-0.03316323459148407,0.16788209974765778,-0.1…
26         abajoues  [-0.026911264285445213,0.19689132273197174,-0…
37   abandonnatrice  [0.017548291012644768,0.10968494415283203,0.21…
38  abandonnatrices  [-0.0036181979812681675,0.16223940253257751,0…
```

```
    Gender  Gender_Label
0        1  Masculine (1)
1        1  Masculine (1)
2        1  Masculine (1)
3        1  Masculine (1)
4        1  Masculine (1)
5        1  Masculine (1)
6        1  Masculine (1)
7        1  Masculine (1)
8        1  Masculine (1)
9        1  Masculine (1)
13       0   Feminine (0)
14       0   Feminine (0)
15       0   Feminine (0)
16       0   Feminine (0)
23       0   Feminine (0)
24       0   Feminine (0)
25       0   Feminine (0)
26       0   Feminine (0)
37       0   Feminine (0)
38       0   Feminine (0)
```

1.5 Test a Simple Perceptron on a Subset of Dataset

1. Load and Prepare the Dataset

[ ]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Perceptron
from sklearn.metrics import accuracy_score, classification_report

# Ensure the dataset is already loaded as df
if 'df' not in globals():
    raise NameError("Dataset 'df' is not defined. Please load it before running␣
 ↪this code.")

# Select 1000 examples from each gender class
sampled_df = df.groupby('Gender').apply(lambda x: x.sample(n=1000,␣
 ↪random_state=42)).reset_index(drop=True)
```

```
<ipython-input-26-434981d7922a>:13: DeprecationWarning: DataFrameGroupBy.apply
operated on the grouping columns. This behavior is deprecated, and in a future
version of pandas the grouping columns will be excluded from the operation.
Either pass `include_groups=False` to exclude the groupings or explicitly select
the grouping columns after groupby to silence this warning.
  sampled_df = df.groupby('Gender').apply(lambda x: x.sample(n=1000,
random_state=42)).reset_index(drop=True)
```

2. Extract Features and Labels

```
[ ]: # Convert embeddings from string format to numerical arrays
X = np.vstack(sampled_df['Embedding'].apply(eval).values)
y = sampled_df['Gender'].values  # Gender labels (0 = Feminine, 1 = Masculine)
```

3. Split the Dataset into Train and Test Sets

```
[ ]: # 80% Training, 20% Testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42, stratify=y)
```

4. Normalize the Feature Data

```
[ ]: # Standardize features using StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

5. Train a Simple Perceptron Model

```
[ ]: # Initialize and train the Perceptron model
perceptron = Perceptron(max_iter=1000, tol=1e-3, random_state=42)
perceptron.fit(X_train, y_train)
```

```
[ ]: Perceptron(random_state=42)
```

6. Evaluate the Model Performance

```
[ ]: # Make predictions on the test set
y_pred = perceptron.predict(X_test)

# Compute accuracy
accuracy = accuracy_score(y_test, y_pred)

# Generate a classification report
report = classification_report(y_test, y_pred)

print(f"Perceptron Accuracy: {accuracy:.4f}")
print("\nClassification Report:\n", report)
```

```
Perceptron Accuracy: 0.8325
```

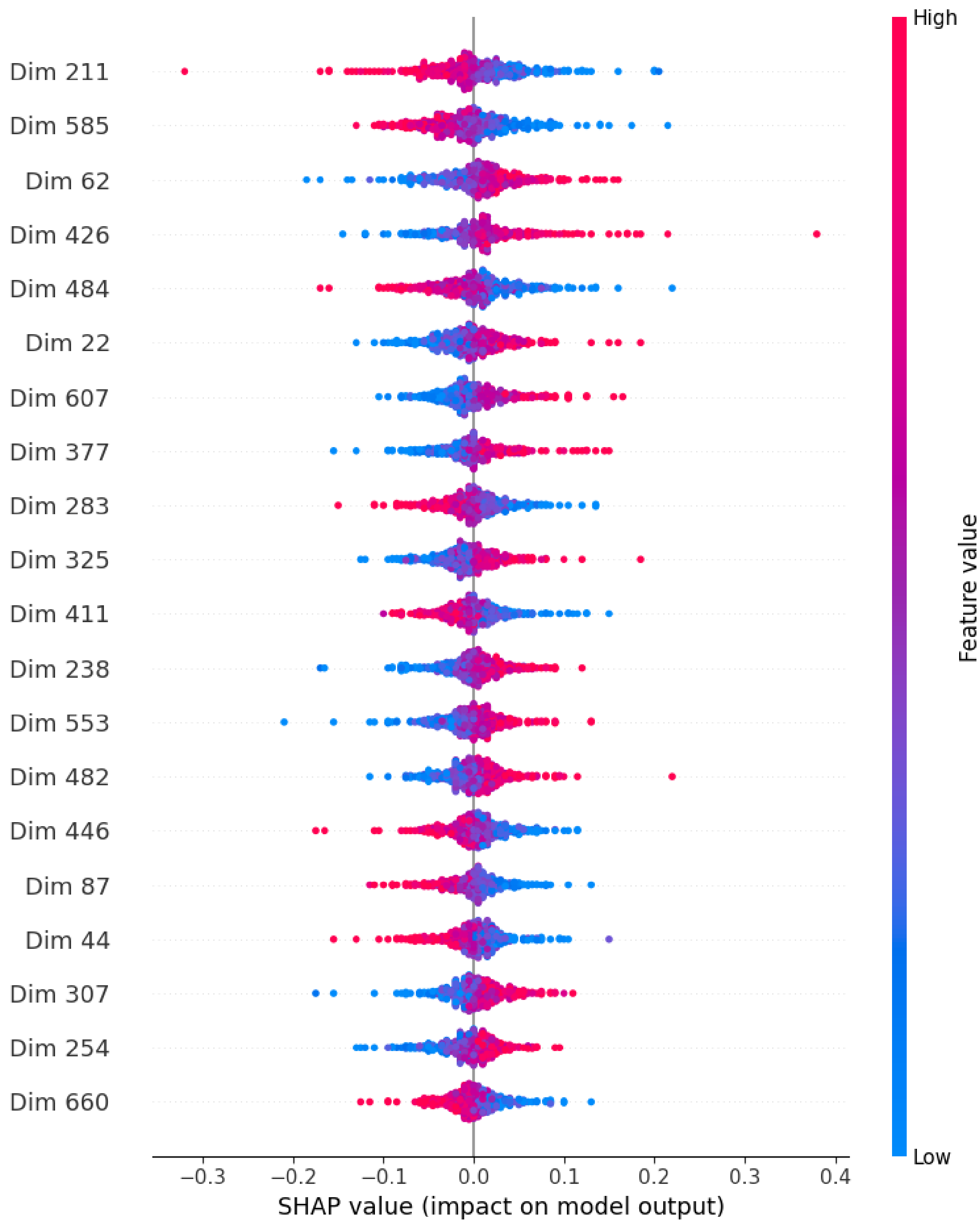
```
Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.85      0.84       200
           1       0.84      0.81      0.83       200

    accuracy                           0.83       400
   macro avg       0.83      0.83      0.83       400
weighted avg       0.83      0.83      0.83       400
```

1.6 Applying SHAP to Understand Global Feature Importance

- Which dimensions in the 768-dimensional embeddings are most important for classification.
- The positive or negative impact of each dimension.

[ ]:
```
import shap

# Create SHAP explainer with max_evals
explainer = shap.Explainer(perceptron.predict, X_test)

# Compute SHAP values
shap_values = explainer(X_test, max_evals=1600)  # Set a higher (2x+1)␣
↪evaluation limit than embeddings length (768)

# Plot feature importance
shap.summary_plot(shap_values, X_test, feature_names=[f"Dim {i}" for i in␣
↪range(768)])
```

```
PermutationExplainer explainer: 401it [10:13,  1.53s/it]
```



1.7 Apply LIME for Local Explanation

- How a specific word's embedding leads to a masculine (1) or feminine (0) classification.
- The percentage contribution of each dimension in individual predictions.

[ ]:
```
!pip install lime
```

```
Collecting lime
  Downloading lime-0.2.0.1.tar.gz (275 kB)
                           275.7/275.7

kB 4.1 MB/s eta 0:00:00
  Preparing metadata (setup.py) … done
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-
packages (from lime) (3.10.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages
(from lime) (1.26.4)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages
(from lime) (1.13.1)
Requirement already satisfied: tqdm in /usr/local/lib/python3.11/dist-packages
(from lime) (4.67.1)
Requirement already satisfied: scikit-learn>=0.18 in
/usr/local/lib/python3.11/dist-packages (from lime) (1.6.1)
Requirement already satisfied: scikit-image>=0.12 in
/usr/local/lib/python3.11/dist-packages (from lime) (0.25.1)
Requirement already satisfied: networkx>=3.0 in /usr/local/lib/python3.11/dist-
packages (from scikit-image>=0.12->lime) (3.4.2)
Requirement already satisfied: pillow>=10.1 in /usr/local/lib/python3.11/dist-
packages (from scikit-image>=0.12->lime) (11.1.0)
Requirement already satisfied: imageio!=2.35.0,>=2.33 in
/usr/local/lib/python3.11/dist-packages (from scikit-image>=0.12->lime) (2.37.0)
Requirement already satisfied: tifffile>=2022.8.12 in
/usr/local/lib/python3.11/dist-packages (from scikit-image>=0.12->lime)
(2025.1.10)
Requirement already satisfied: packaging>=21 in /usr/local/lib/python3.11/dist-
packages (from scikit-image>=0.12->lime) (24.2)
Requirement already satisfied: lazy-loader>=0.4 in
/usr/local/lib/python3.11/dist-packages (from scikit-image>=0.12->lime) (0.4)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-
packages (from scikit-learn>=0.18->lime) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.11/dist-packages (from scikit-learn>=0.18->lime) (3.5.0)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib->lime) (1.3.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-
packages (from matplotlib->lime) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.11/dist-packages (from matplotlib->lime) (4.55.8)
Requirement already satisfied: kiwisolver>=1.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib->lime) (1.4.8)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib->lime) (3.2.1)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.11/dist-packages (from matplotlib->lime) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-
```

```
packages (from python-dateutil>=2.7->matplotlib->lime) (1.17.0)
Building wheels for collected packages: lime
  Building wheel for lime (setup.py) … done
  Created wheel for lime: filename=lime-0.2.0.1-py3-none-any.whl size=283834
sha256=c808a8d15d002ce6de525199fd9ed4c88a64e5aea9f3db7365d0e7dbfc9672e4
  Stored in directory: /root/.cache/pip/wheels/85/fa/a3/9c2d44c9f3cd77cf4e533b58
900b2bf4487f2a17e8ec212a3d
Successfully built lime
Installing collected packages: lime
Successfully installed lime-0.2.0.1
```

1.7.1 Test LIME on a single word

[ ]:
```
import lime
import lime.lime_tabular
import numpy as np

# Create a LIME explainer
explainer = lime.lime_tabular.LimeTabularExplainer(
    X_train,
    feature_names=[f"Dim {i}" for i in range(768)],
    class_names=["Feminine", "Masculine"],
    mode="classification"
)

# Pick a test instance (e.g., first example)
test_instance = X_test[0].reshape(1, -1)

# Define a wrapper function for LIME
def perceptron_predict(X):
    return np.column_stack([(perceptron.decision_function(X) > 0).astype(int),
                            (perceptron.decision_function(X) <= 0).astype(int)])

# Explain the prediction for this instance
exp = explainer.explain_instance(test_instance[0], perceptron_predict)

# Show the explanation
exp.show_in_notebook()
```

```
<IPython.core.display.HTML object>
```

1.7.2 Test LIME on 100 words to get top 20 contributing dimensions

[ ]:
```
import lime
import lime.lime_tabular
import numpy as np
from collections import Counter
import re  # Import regex module
```

```python
# Create a LIME explainer
explainer = lime.lime_tabular.LimeTabularExplainer(
    X_train,
    feature_names=[f"Dim {i}" for i in range(768)],
    class_names=["Feminine", "Masculine"],
    mode="classification"
)

# Function to apply LIME to multiple words
top_features = Counter()

for i in range(min(100, len(X_test))):  # Test on first 100 words (words length␣
↪is adjustable)
    test_instance = X_test[i].reshape(1, -1)

    def perceptron_predict(X):
        return np.column_stack([(perceptron.decision_function(X) > 0).
↪astype(int),
                                (perceptron.decision_function(X) <= 0).
↪astype(int)])

    # Explain instance
    exp = explainer.explain_instance(test_instance[0], perceptron_predict)

    # Collect important features
    for feature, weight in exp.as_list():
        # Extract numerical dimension index using regex
        match = re.search(r'\d+', feature)
        if match:
            dim_index = int(match.group())  # Extract numeric part
            top_features[dim_index] += abs(weight)  # Store absolute importance␣
↪(handle negative LIME value)

# Convert to sorted list of most important features
sorted_features = sorted(top_features.items(), key=lambda x: x[1], reverse=True)

# Display top 20 most important dimensions
print("Top 20 most important dimensions across multiple words:")
for dim, importance in sorted_features[:20]:
    print(f"Dim {dim}: {importance:.3f}")
```

```
Top 20 most important dimensions across multiple words:
Dim 211: 3.280
Dim 62: 2.681
Dim 585: 2.535
Dim 22: 2.375
```

```
Dim 484: 2.236
Dim 426: 2.139
Dim 238: 1.720
Dim 482: 1.481
Dim 411: 1.390
Dim 377: 1.177
Dim 307: 1.165
Dim 283: 1.131
Dim 115: 1.130
Dim 87: 1.101
Dim 553: 0.990
Dim 107: 0.990
Dim 480: 0.978
Dim 607: 0.971
Dim 68: 0.927
Dim 516: 0.872
```

1.8 Extract & Compare SHAP and LIME High-Impact Dimensions

[ ]:

```
import pandas as pd
import numpy as np
from collections import Counter

# Calculate mean absolute SHAP value for each dimension
shap_importance = np.abs(shap_values.values).mean(axis=0)

# Get top 20 dimensions from SHAP with their importance scores
top_shap_dimensions = sorted(
    [(dim, shap_importance[dim]) for dim in np.argsort(shap_importance)[-20:]],
    key=lambda x: x[1], reverse=True
)

# Get top 20 dimensions from LIME with their importance scores
sorted_lime_features = sorted(top_features.items(), key=lambda x: x[1],␣
 ↪reverse=True)
top_lime_dimensions = sorted_lime_features[:20]

# Extract just the dimension indices
top_shap_indices = [dim[0] for dim in top_shap_dimensions]
top_lime_indices = [dim[0] for dim in top_lime_dimensions]

# Find matching dimensions between SHAP and LIME
matching_dimensions = list(set(top_shap_indices) & set(top_lime_indices))

# Find dimensions unique to each method
unique_to_shap = list(set(top_shap_indices) - set(top_lime_indices))
unique_to_lime = list(set(top_lime_indices) - set(top_shap_indices))
```

```python
# Prepare data for table with importance scores
comparison_data = []
for dim in sorted(set(top_shap_indices + top_lime_indices)):
    shap_score = next((s[1] for s in top_shap_dimensions if s[0] == dim), 0.0) ␣
↪# Replace NaN with 0.0
    lime_score = next((l[1] for l in top_lime_dimensions if l[0] == dim), 0.0) ␣
↪# Replace NaN with 0.0
    overall_importance = shap_score + lime_score  # Combine SHAP & LIME␣
↪importance scores
    comparison_data.append({
        "Dimension": dim,
        "SHAP Importance": shap_score,
        "LIME Importance": lime_score,
        "Overall Importance": overall_importance  # New column
    })

# Create DataFrame for display
comparison_table = pd.DataFrame(comparison_data)

# Sort by Overall Importance (descending order)
comparison_table = comparison_table.sort_values(by="Overall Importance",␣
↪ascending=False)

# Display the comparison table
from IPython.display import display
print("\nSHAP & LIME Feature Comparison Table:")
display(comparison_table)
```

SHAP & LIME Feature Comparison Table:

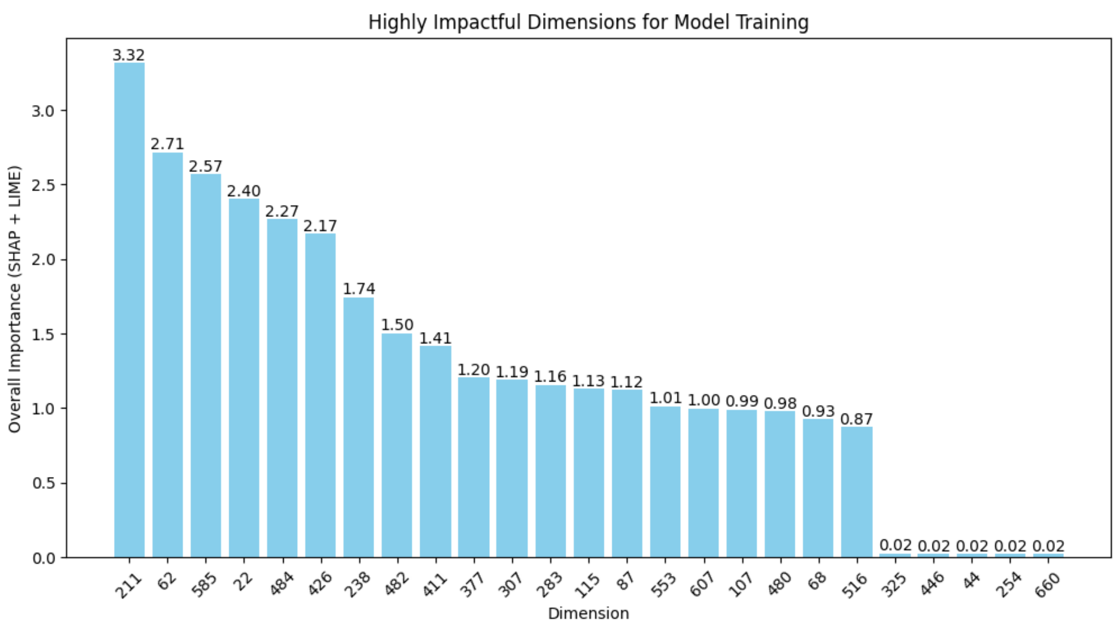
	Dimension	SHAP Importance	LIME Importance	Overall Importance
7	211	0.035188	3.280233	3.315420
2	62	0.032488	2.681485	2.713973
22	585	0.032587	2.535049	2.567636
0	22	0.027487	2.375404	2.402892
19	484	0.030488	2.236443	2.266930
15	426	0.031425	2.139282	2.170707
8	238	0.023525	1.720006	1.743531
18	482	0.022962	1.480601	1.503564
14	411	0.023762	1.390037	1.413799
13	377	0.025487	1.177291	1.202779
11	307	0.022587	1.165008	1.187596
10	283	0.024725	1.130884	1.155609
6	115	0.000000	1.130208	1.130208
4	87	0.022875	1.100710	1.123585
21	553	0.023375	0.990150	1.013525

23	607	0.025975	0.970675	0.996650
5	107	0.000000	0.989835	0.989835
17	480	0.000000	0.978161	0.978161
3	68	0.000000	0.926817	0.926817
20	516	0.000000	0.871713	0.871713
12	325	0.024375	0.000000	0.024375
16	446	0.022912	0.000000	0.022912
1	44	0.022750	0.000000	0.022750
9	254	0.022525	0.000000	0.022525
24	660	0.022050	0.000000	0.022050

1.8.1 Extract High-Impact Dimensions Based on SHAP and LIME Importance

[ ]:
```
import matplotlib.pyplot as plt

# Prioritize matching dimensions & strongest unique dimensions
high_impact_dimensions = matching_dimensions + unique_to_shap[:5] +␣
↪unique_to_lime[:5]

# Store highly impactful dimensions with their importance scores
high_impact_data = []
for dim in high_impact_dimensions:
    shap_score = next((s[1] for s in top_shap_dimensions if s[0] == dim), 0.0) ␣
↪# Replace NaN with 0.0
    lime_score = next((l[1] for l in top_lime_dimensions if l[0] == dim), 0.0) ␣
↪# Replace NaN with 0.0
    overall_importance = shap_score + lime_score  # Sum SHAP & LIME scores
    high_impact_data.append({"Dimension": dim, "Overall Importance":␣
↪overall_importance})

# Convert to DataFrame and sort by Overall Importance
high_impact_df = pd.DataFrame(high_impact_data).sort_values(by="Overall␣
↪Importance", ascending=False)

# Store the top impactful dimensions for later Perceptron training
selected_dimensions = high_impact_df["Dimension"].tolist()

# Plot Bar Chart of Highly Impactful Dimensions
plt.figure(figsize=(12, 6))
plt.bar(high_impact_df["Dimension"].astype(str), high_impact_df["Overall␣
↪Importance"], color="skyblue")
plt.xlabel("Dimension")
plt.ylabel("Overall Importance (SHAP + LIME)")
plt.title("Highly Impactful Dimensions for Model Training")

# Add data labels above bars
for i, value in enumerate(high_impact_df["Overall Importance"]):
```

```
    plt.text(i, value + 0.02, f"{value:.2f}", ha='center', fontsize=10)

plt.xticks(rotation=45)
plt.show()

# Print highly-impactful dimensions
print("\nHighly Impactful Dimensions Based on SHAP and LIME Importance:")
print(selected_dimensions)
```




```
Highly Impactful Dimensions Based on SHAP and LIME Importance:
[211, 62, 585, 22, 484, 426, 238, 482, 411, 377, 307, 283, 115, 87, 553, 607,
107, 480, 68, 516, 325, 446, 44, 254, 660]
```

1.9 Retraining Perceptron with High-Impact Selected Dimensions & Comparing Results

1. Load and Prepare the Dataset

[ ]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Perceptron
from sklearn.metrics import accuracy_score, classification_report

# Ensure the dataset is already loaded as df
```

```
if 'df' not in globals():
    raise NameError("Dataset 'df' is not defined. Please load it before running␣
 ↪this code.")

# Select 1000 examples from each gender class
sampled_df = df.groupby('Gender').apply(lambda x: x.sample(n=1000,␣
 ↪random_state=42)).reset_index(drop=True)
```

```
<ipython-input-65-434981d7922a>:13: DeprecationWarning: DataFrameGroupBy.apply
operated on the grouping columns. This behavior is deprecated, and in a future
version of pandas the grouping columns will be excluded from the operation.
Either pass `include_groups=False` to exclude the groupings or explicitly select
the grouping columns after groupby to silence this warning.
  sampled_df = df.groupby('Gender').apply(lambda x: x.sample(n=1000,
random_state=42)).reset_index(drop=True)
```

2. Extract Features and Labels

[ ]:
```
# Convert embeddings from string format to numerical arrays
X = np.vstack(sampled_df['Embedding'].apply(eval).values)
y = sampled_df['Gender'].values  # Gender labels (0 = Feminine, 1 = Masculine)
```

3. Extract only the selected impactful dimensions

[ ]:
```
X_selected = X[:, selected_dimensions]  # Use only selected dimensions
```

4. Split the Dataset into Train and Test Sets

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X_selected, y, test_size=0.
 ↪2, random_state=42, stratify=y)
```

5. Normalize the selected feature data

[ ]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

6. Train a new Perceptron model with selected dimensions

[ ]:
```
perceptron_selected = Perceptron(max_iter=1000, tol=1e-3, random_state=42)
perceptron_selected.fit(X_train, y_train)
```

[ ]:
```
Perceptron(random_state=42)
```

7. Evaluate the New Perceptron Performance

[ ]:
```
# Evaluate the new Perceptron model
y_pred_selected = perceptron_selected.predict(X_test)

# Compute accuracy
```

```
accuracy_selected = accuracy_score(y_test, y_pred_selected)

# Generate classification report
report_selected = classification_report(y_test, y_pred_selected)

print(f"Perceptron Accuracy (Selected Features): {accuracy_selected:.4f}")
print("\nClassification Report (Selected Features):\n", report_selected)
```

```
Perceptron Accuracy (Selected Features): 0.6650

Classification Report (Selected Features):
               precision    recall  f1-score   support

           0       0.67      0.65      0.66       200
           1       0.66      0.68      0.67       200

    accuracy                           0.67       400
   macro avg       0.67      0.67      0.66       400
weighted avg       0.67      0.67      0.66       400
```

8. Compare the New Perceptron (25 Dimensinos) with the Previous Perceptron (768 Dimensions) Results

[ ]:
```
import matplotlib.pyplot as plt

print("\nComparison with Previous Perceptron:")
print(f"Previous Perceptron (768 Dimensions) Accuracy: {accuracy:.4f}")
print(f"New Perceptron (25 Dimensions) Accuracy (Selected Features):␣
↪{accuracy_selected:.4f}")

# Data for visualization
models = ["Previous Perceptron (768 Dimensions)", "New Perceptron (Selected 25␣
↪Dimensions)"]
accuracies = [accuracy, accuracy_selected]

# Create bar chart
plt.figure(figsize=(8, 5))
plt.bar(models, accuracies, color=["gray", "skyblue"])

# Add data labels
for i, value in enumerate(accuracies):
    plt.text(i, value + 0.005, f"{value:.4f}", ha='center', fontsize=12,␣
↪fontweight='bold')

# Labels and title
plt.ylabel("Accuracy")
plt.title("Comparison of Perceptron Accuracy")
```

```python
# Show the plot
plt.ylim(0, 1)  # Ensure the y-axis is between 0 and 1 for proper scale
plt.show()
```

```
Comparison with Previous Perceptron:
Previous Perceptron (768 Dimensions) Accuracy: 0.8325
New Perceptron (25 Dimensions) Accuracy (Selected Features): 0.6650
```