French Noun Gender & Adjective Gender Prediction using MLP & Feature Importance

Last Meeting Recap:

We've confirmed our hypothesis that gender information is both encoded in word embeddings and retrievable through classification. The next step is to investigate where this information is stored, specifically, if certain embedding dimensions encode gender. Going forward, we'll focus on SHAP for interpretability and use MLP and Logistic Regression as classifiers, comparing results across nouns and adjectives.

1. Introduction:

This experiment explores how symbolic lexical information (gender) is embedded within French word embeddings. Using several FlauBERT-based models, we:

- Train classifiers to predict gender (masculine vs. feminine)
- Analyze feature importance using SHAP (SHapley Additive exPlanations)

2. Approach:

- **Embedding Models Used:** Variants of FlauBERT (base cased, base uncased, large uncased, small cased).
- **Classifier**: Multi-Layer Perceptron (MLP).
- **Feature Analysis:** SHAP for feature importance and selection.

3. Methodology:

3.1 Data Preprocessing:

- **Class Balancing:** Balanced gender classes by using the undersampling method
- **Splitting:** 80% training, 20% testing with stratified sampling.
- **Normalization:** Applied StandardScaler.
- **Dataset :** 100% of the available data used for training.

3.2 MLP Classifier Architecture:

- **Input:** Word embeddings.
- **Hidden Layer**: 100 neurons with ReLU activation and 20% dropout.
- **Output**: 1 neuron for binary classification (masculine/feminine).

3.3 Training Setup:

- Optimizer: Adam (learning rate = 0.001).
- Loss Function: Binary CrossEntropy.
- Epochs: 20.
- Batch Size: 32.
- Early Stopping: Based on validation accuracy.

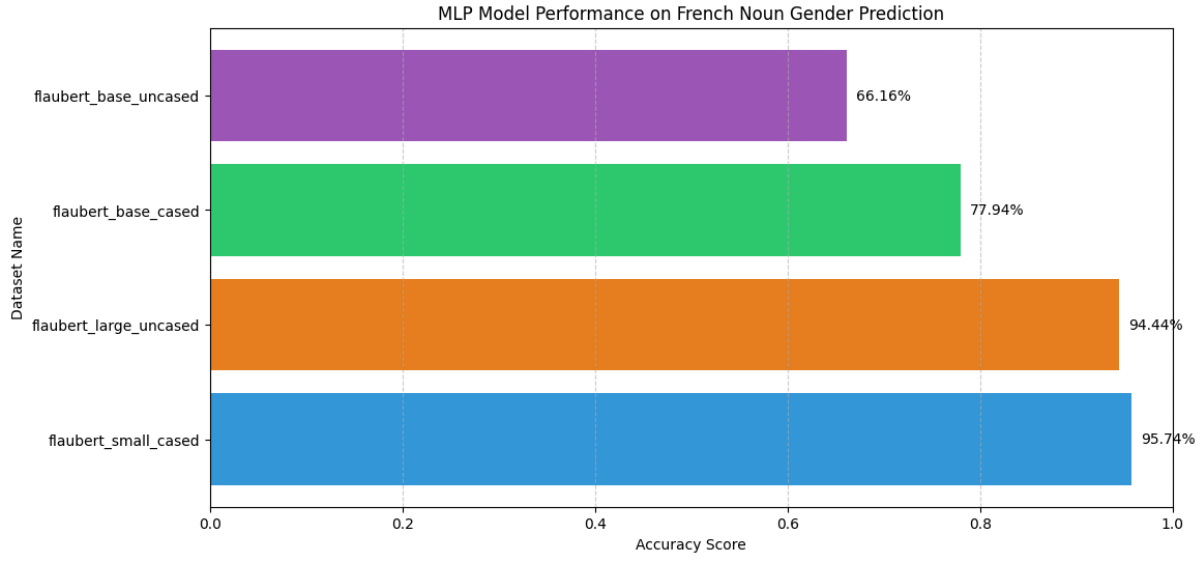
4. Model Evaluation:

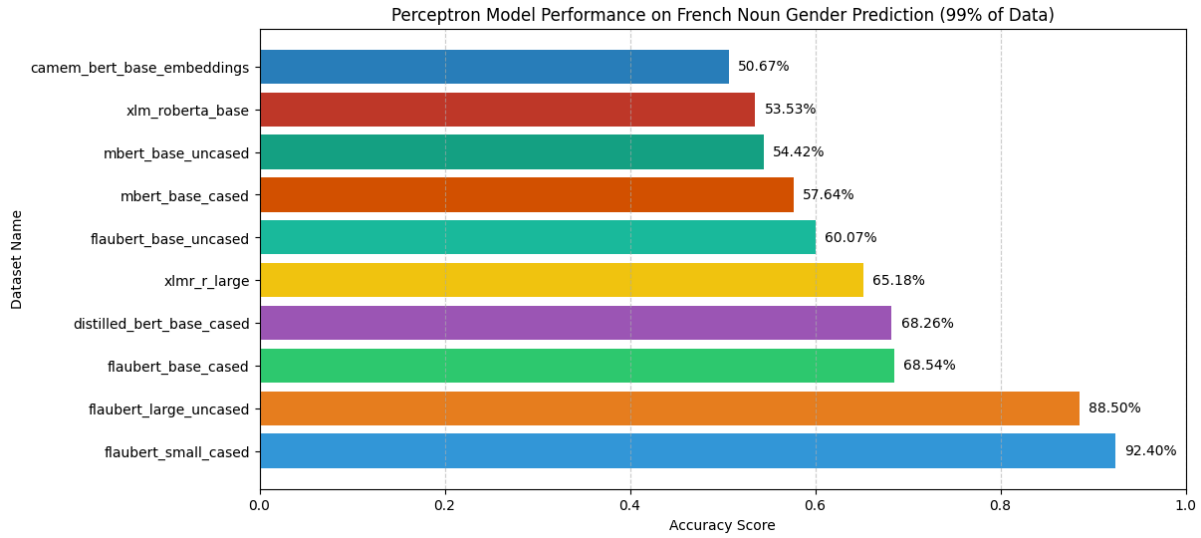
4.1 MLP Classifier Performance:

- Achieved high accuracy, particularly with *flaubert_small_cased* (95.7%) and *flaubert_large_uncased* (94.4%).

4.2 Perceptron Performance:

- Performance ranged from ~50% to 68%.
- Indicates that more complex models (MLP) can better leverage gender-encoded information in embeddings.





ANALYSIS:

The two charts clearly show that using a Multi-Layer Perceptron (MLP) significantly improves model performance compared to the simple Perceptron:

- MLP Classifier (Chart 1) – On full dataset (100%): High accuracy across all variants, with a clear boost compared to the Perceptron model.
- Simple Perceptron (Chart 2) – On 99% of the data:Reasonable performance, but consistently lower than the MLP version.

Conclusion:

- MLP outperforms the Perceptron across all models, especially for base models, where the gap is significant (+9% for flaubert_base_cased).
- The performance confirms the hypothesis: a more complex classifier like MLP can better capture the gender information encoded in the word embeddings.

5. SHAP Feature Analysis:

Objective:

Evaluate how well SHAP-selected features retain classification power.

Methodology:

- Compute SHAP importance for each embedding dimension.
- Select top N% of dimensions (1%, 2%, 4%).
- Retrain a Multi-Layer Perceptron (MLP) with only those features.
- Compare with baseline MLP trained on full embeddings.

Methodology Details:

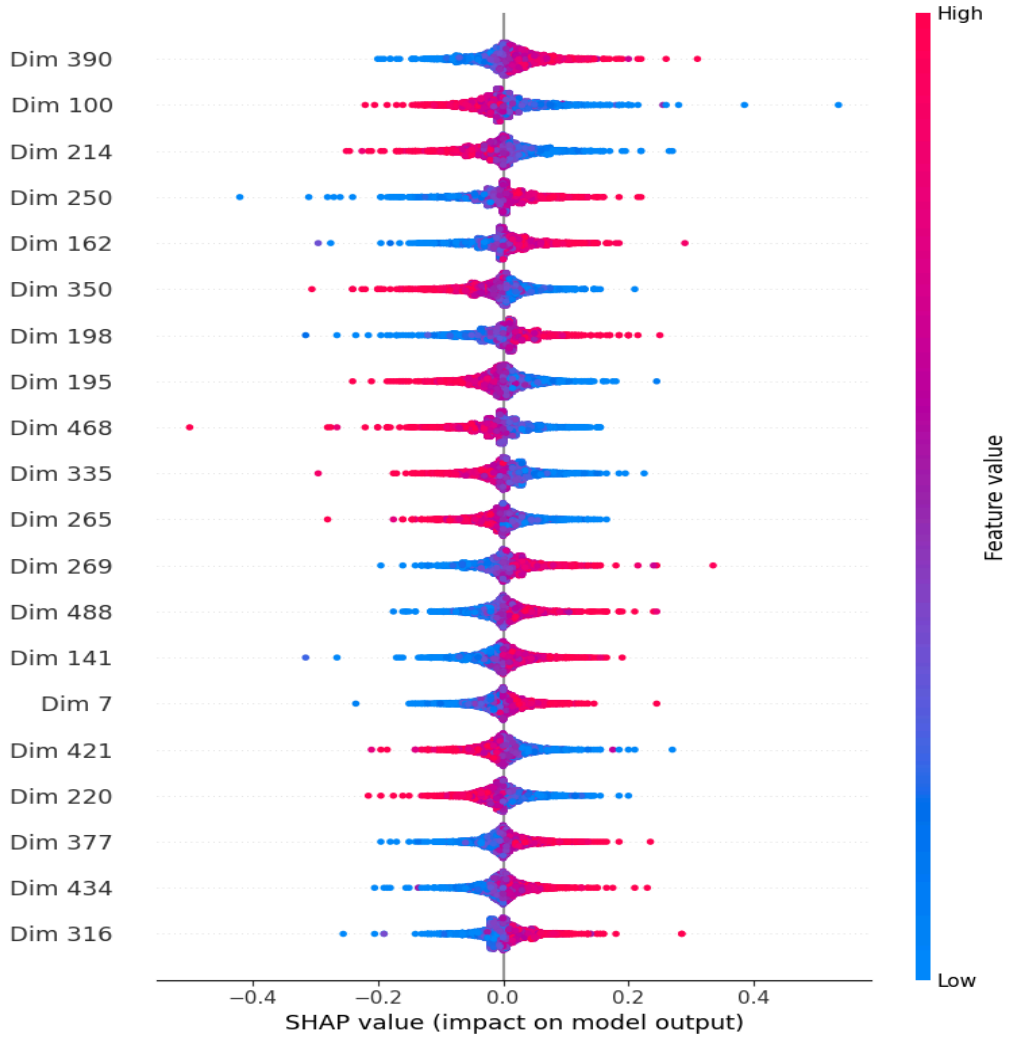
1. Apply SHAP on the Trained MLP:

- Use shap.Explainer(model.predict, X_test) on the MLP models (already trained on each dataset).

- Shap computed impact scores per embedding dimension
- Use the same input structure as in the Perceptron case.

2. Visualization and Interpretation:

- Create summary plots to show:
    - Which dimensions contribute most to gender prediction.
    - How values of those dimensions affect predictions.



How to Read This SHAP Feature Importance Plot:

- Each row = one embedding dimension (Dim 390, Dim 100...).
- Each dot = a single word in the test set.
- X-axis (SHAP value) = how much that dimension impacts the model's gender prediction (positive or negative).
- Right (→): pushes prediction toward masculine.

- Left (←): pushes prediction toward feminine.
- Color = actual feature value for the dimension:

  🔴 Red = high value of that dimension -> masculine

  🔵 Blue = low value -> feminine

ANALYSIS:

Top Predictive Dimensions:

- Dimensions at the top (Dim 390, 100, 214) are the most important for gender noun prediction.
- These features contribute the most to the model's decision.

Direction of Influence

- For example, in Dim 390, blue (low value) mostly pushes prediction left (toward feminine), red (high) pushes right (toward masculine).
- So this dimension helps distinguish gender.

Encoding Insight:

- Gender seems to be encoded in a small subset of dimensions (20 out of ~768 or 1024).
- This supports the hypothesis that gender information is localized in certain embedding dimensions.

Some features have both positive & negative impacts, meaning their importance depends on the word's embedding value.

SHAP Feature CSV:

- Exported global SHAP values to CSV.
- Each model (flaubert_base_cased, flaubert_small_cased, etc.) has a different number of embedding dimensions (768 vs 1024). So:
  - Some features (Dim 994, Dim 996) don't exist in all models.
  - When aggregating across all models, missing dimensions are filled with NaN.

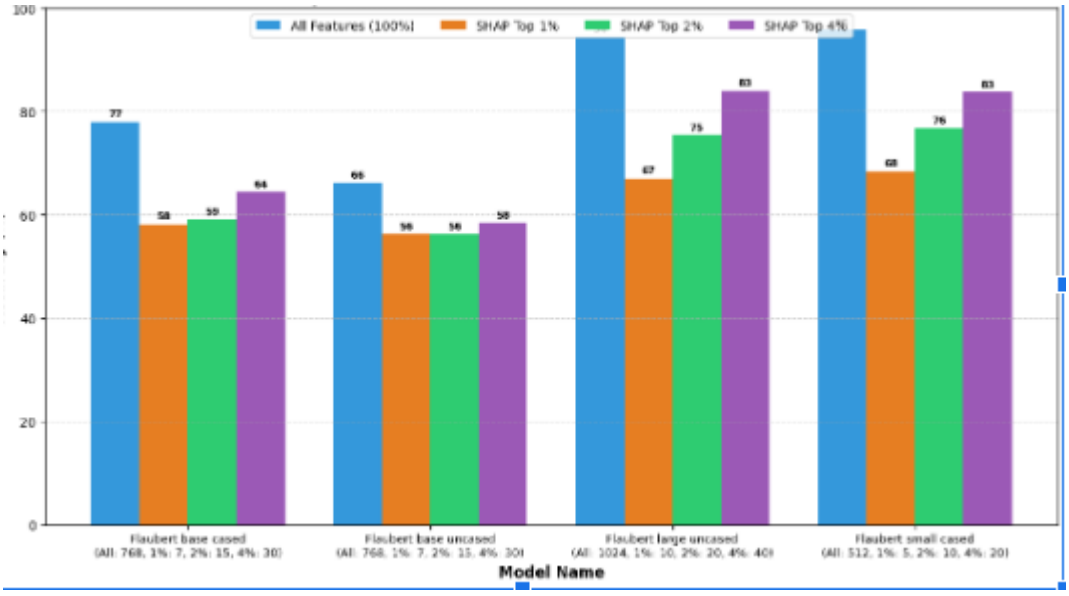
	Feature	flaubert_base_cased	flaubert_base_uncased	flaubert_large_uncased	flaubert_small_cased	Mean Importance
752	Dim 752	0.024323	0.040974	0.007429	NaN	0.024242
668	Dim 668	0.028276	0.028154	0.009449	NaN	0.021960
664	Dim 664	0.034488	0.018566	0.004494	NaN	0.019183
630	Dim 630	0.018248	0.036437	0.002773	NaN	0.019153
256	Dim 256	0.008700	0.030603	0.012549	0.020925	0.018194
587	Dim 587	0.045360	0.007513	0.001641	NaN	0.018171
350	Dim 350	0.020363	0.006048	0.014082	0.031281	0.017944
214	Dim 214	0.004957	0.028638	0.004857	0.032759	0.017803
717	Dim 717	0.023241	0.026860	0.003139	NaN	0.017746
994	Dim 994	NaN	NaN	0.017646	NaN	0.017646
996	Dim 996	NaN	NaN	0.017573	NaN	0.017573
570	Dim 570	0.022395	0.024194	0.005352	NaN	0.017314
644	Dim 644	0.018178	0.028090	0.005113	NaN	0.017127
177	Dim 177	0.017490	0.022963	0.007892	0.019210	0.016889
27	Dim 27	0.018178	0.033853	0.011318	0.002868	0.016554
543	Dim 543	0.025421	0.015842	0.007877	NaN	0.016380
468	Dim 468	0.012640	0.019914	0.003734	0.029088	0.016344

3. Select Top N% SHAP Features:

- For each model, features were ranked based on mean absolute SHAP values.
- Selected the top 1%, 2%, and 4% most important dimensions.
- Reduced datasets were created using only these top features.
- Feature names like "Dim 350" were mapped to column indices like "350."

4. Retrain MLP with Top Features:

- Retrain MLP using only SHAP-selected features.
- Model architecture: one hidden layer with 100 neurons, early stopping enabled.
- Compared performance against the baseline model trained on all features.



The bar chart compares the accuracy of the MLP classifier when using:

- All Features (100%) – full embedding dimensions.
- SHAP-Selected Features (Top 1%, 2%, and 4%) – only the most important features as ranked by SHAP values.
- Each Flaubert model is evaluated under these conditions.

6. Results & Analysis:

- Accuracy decreases with only 1% of features (Flaubert base cased: 77% → 58%).
- Accuracy improves with 2% and 4% of features (Flaubert large uncased: 67% → 83%).
- Top 4% of SHAP-selected features deliver performance nearly matching full-feature models.
- Flaubert small and large variants encode gender more compactly.
- Base models (flaubert_base_cased/uncased) need more dimensions to perform well.

Model	Full accuracy	Top 4% accuracy	Drop
Flaubert-small-cased	**96%**	**83%**	**Only 13%**
Flaubert-large-uncased	**96%**	**83%**	**Same approximately**
Flaubert-base-cased	**77%**	**64%**	**More sensitive to reduction**
Flaubert-base-uncased	**66%**	**58%**	**Weak under feature reduction**

Evaluate the Results:

- Does the model retain high accuracy with fewer features?

✔ Yes, especially with the top 4% SHAP-selected features.

- High-performing models like `flaubert_small_cased` and `flaubert_large_uncased` retain ~83%+ accuracy, very close to their full-feature performance.
- This proves that a small subset of dimensions is sufficient to achieve strong prediction results.

- Which models encode gender more compactly (fewer features with high performance)?

✔ Flaubert small cased and Flaubert large uncased are the most compact.

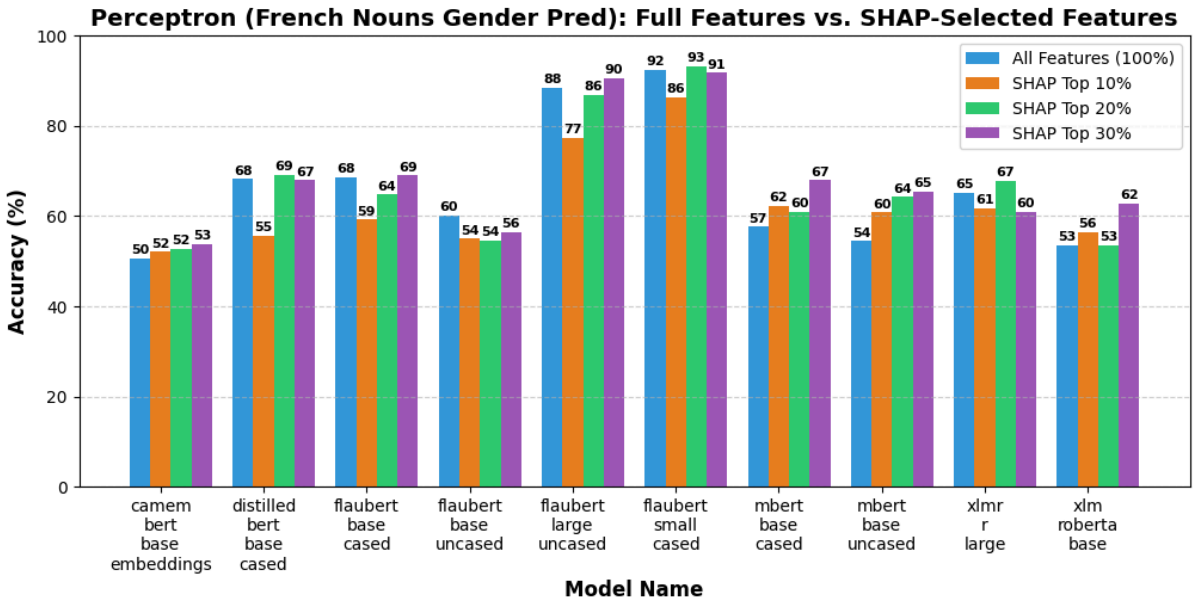
- They maintain high accuracy even with just 4% of the features.

- This suggests these models have denser, more localized representations of gender information.

✔ In contrast, base models like `flaubert_base_cased` need more dimensions to reach the same performance, indicating gender is spread across more features.

Models like `flaubert_small_cased` and `flaubert_large_uncased` encode gender more compactly. SHAP successfully identifies these critical dimensions, showing that just a few features (as low as 4%) are enough to retain high accuracy especially in well-structured, monolingual models.

7. Comparison:Current SHAP experiment (with 100% training data) and the previous one (99% training data)



Reminder the Goal of the New SHAP Experiment:To test if a very small subset of features (1%, 2%, 4%) is enough to retain high classification performance.

This helps answer the hypothesis:

“Can SHAP select a compact subset of informative features when using a stronger classifier (MLP) trained on 100% of the data?”

Key Differences Between the Two SHAP Experiments:

	Previous Shap experiment	**New Shap experiment**

Classifier	Perceptron	MLP
Training Data	99% of the dataset	100% of the dataset
Shap features size	Top 10,20,30%	Top 1,2,4%

Model	Full (Perceptron)	SHAP 10%	SHAP 20%	SHAP 30%	Full (MLP)	SHAP 1%	SHAP 2%	SHAP 4%
flaubert_base_cased	68%	59%	64%	69%	77%	58%	59%	64%
flaubert_base_uncased	60%	54%	54%	56%	66%	56%	56%	58%
flaubert_large_uncased	88%	77%	90%	86%	94%	67%	75%	83%
flaubert_small_cased	92%	73%	89%	91%	95%	68%	76%	83%

ANALYSIS:

Performance Drop with Few Features:

- MLP (New): Shows good performance even with just 4% of features (83% for Flaubert-small/large).

- Perceptron (Old): Needs 10–30% to achieve similar accuracy. Below that, the performance drops significantly.

Stronger Classifier :

- MLP is better at leveraging compact SHAP subsets (1–4%) than Perceptron is with 10–30%.
- Indicates the classifier matters: with better non-linear modeling capacity, MLP can make better use of fewer but more relevant features.

Feature Set Size Matters Less with Good Embeddings:

- For Flaubert-large and Flaubert-small, even 1–2% of SHAP-selected features are enough to maintain high accuracy (close to 95%).

- Suggests these embeddings encode gender very efficiently.

8. Evidence for the Hypothesis:

- If performance stays high with a few features, the classifier is effectively using gender cues encoded in specific embedding dimensions.

SHAP Feature Indexes Summary:
We generated a summary table listing the selected feature index numbers (dimensions) for each model's top N% SHAP-ranked features. This ensures transparency in feature selection and allows reproducibility.

Key details:

- The total number of valid features (non-NaN SHAP values) per model.
- The expected vs. actual feature count for each SHAP selection threshold (1%, 2%, 4%).
- The corresponding feature index numbers extracted from SHAP rankings.
- This table, saved as "shap_top_nouns_gender_feature_indexes_summary.csv," provides a reference for analyzing which embedding dimensions were most influential in predicting gender.

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Combined SHAP Feature Index Table Saved as 'shap_top_feature_indexes_summary.csv'
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	Model	Top %	Total Features	Top % Feature Count	Feature Indexes
0	flaubert_base_cased	1%	768	7	5, 31, 102, 132, 21, 2, 27, 128, 45, 167
1	flaubert_base_cased	2%	768	15	5, 31, 102, 132, 21, 2, 27, 128, 45, 167, 64, ...
2	flaubert_base_cased	4%	768	30	5, 31, 102, 132, 21, 2, 27, 128, 45, 167, 64, ...
3	flaubert_base_uncased	1%	768	7	0, 3, 62, 14, 34, 68, 84, 164, 100, 20
4	flaubert_base_uncased	2%	768	15	0, 3, 62, 14, 34, 68, 84, 164, 100, 20, 95, 4,...
5	flaubert_base_uncased	4%	768	30	0, 3, 62, 14, 34, 68, 84, 164, 100, 20, 95, 4,...
6	flaubert_large_uncased	1%	1024	10	24, 9, 10, 249, 26, 113, 398, 52, 6, 61
7	flaubert_large_uncased	2%	1024	20	24, 9, 10, 249, 26, 113, 398, 52, 6, 61, 69, 9...
8	flaubert_large_uncased	4%	1024	40	24, 9, 10, 249, 26, 113, 398, 52, 6, 61, 69, 9...
9	flaubert_small_cased	1%	512	5	54, 23, 7, 51, 114, 6, 28, 73, 16, 47
10	flaubert_small_cased	2%	512	10	54, 23, 7, 51, 114, 6, 28, 73, 16, 47, 80, 59,...
11	flaubert_small_cased	4%	512	20	54, 23, 7, 51, 114, 6, 28, 73, 16, 47, 80, 59,...

This table shows which specific dimensions (Dim 5, 31, 102...) were selected for each SHAP Top N% threshold.it Confirms that Top N% selection yields the expected number of dimensions (7 for 1% of 768).

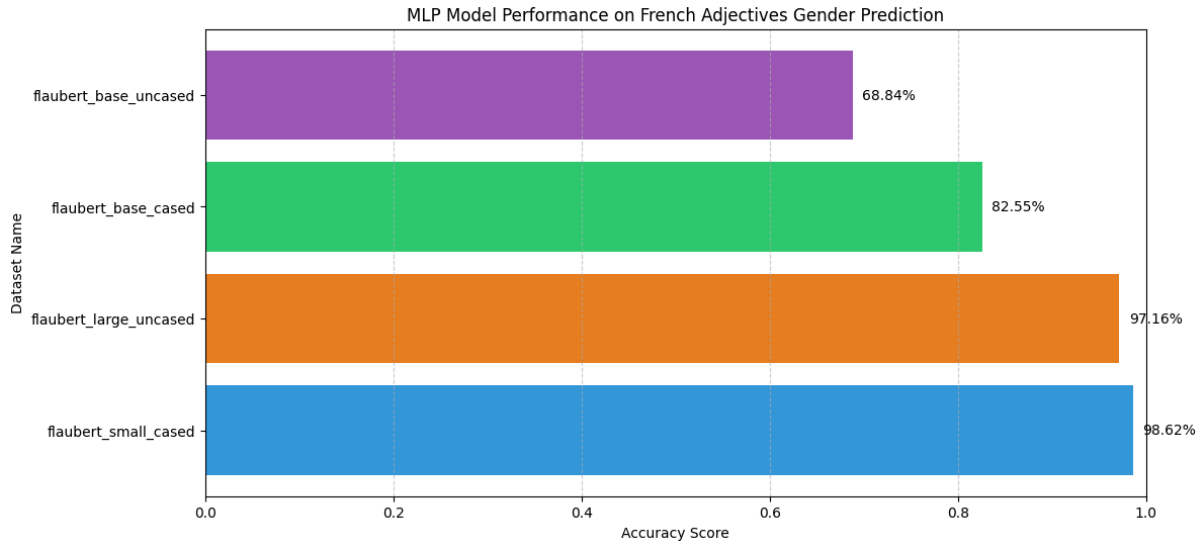
We can now compare the feature indices across models to:

- Identify common dimensions that appear frequently
- Spot models that require more dispersed features to perform well.

9. Adjective Gender Prediction:

- Same goal: explore how gender is encoded in adjective embeddings
- Used same MLP classifier + SHAP analysis
- Based on 4 Flaubert models
- Motivation: adjectives differ from nouns morphologically, does this affect gender encoding?

10. Performance with Full Embeddings (100%):



The bar chart shows the classification accuracy for predicting gender of French adjectives using full word embeddings from different Flaubert models: Flaubert Small Cased achieves the highest accuracy at 98.6%.

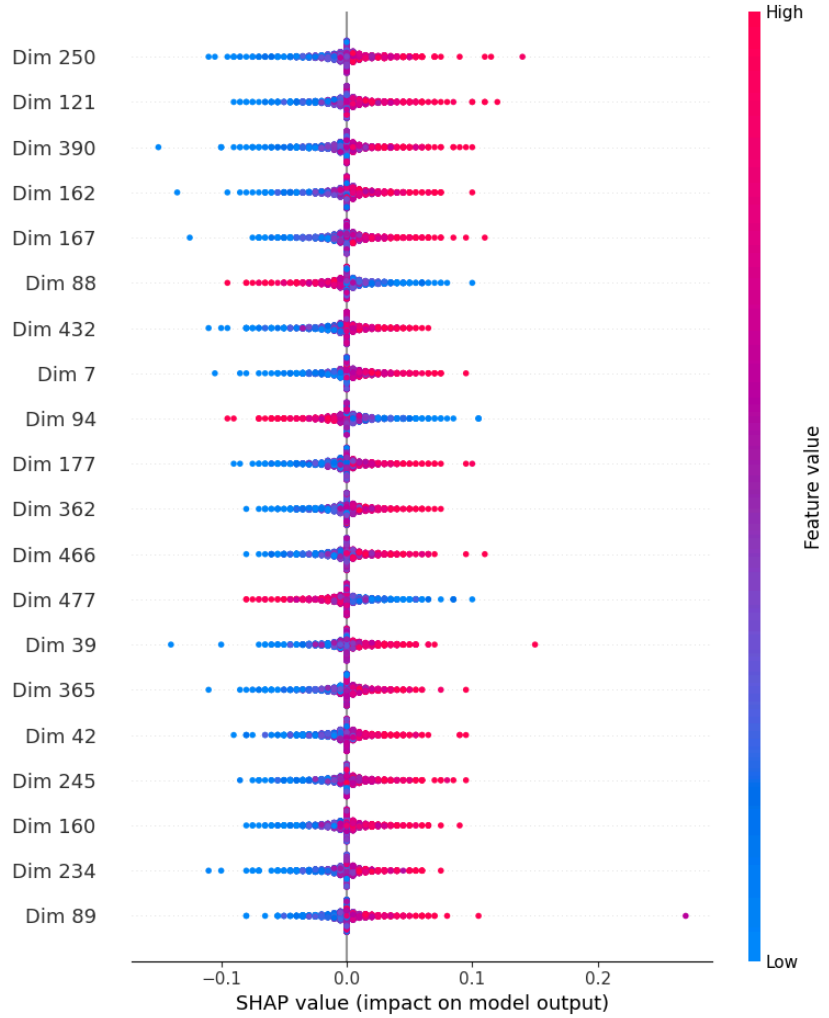
ANALYSIS Noun vs. Adjective Performance Comparison:

- Adjectives are consistently easier to predict than nouns: all models perform slightly better on adjectives.
- Morphological regularity in adjectives (endings like -eux vs -euse) may explain higher performance, this form-based regularity makes the gender signal stronger in embeddings.

- Top models (small/large) maintain very high accuracy on both tasks, confirming their strong embedding quality and compact gender encoding.
- Base models struggle more but still improve slightly from nouns to adjectives, again showing that adjectives might offer clearer gender cues.

11. SHAP-Based Feature Selection for Adjectives:

- Applied same SHAP pipeline (1%, 2%, 4%)
- Retrained MLP on reduced dimensions
- Performance drops at 1%, improves at 4% (`flaubert_small_cased`: 96% → 83%)



--- SHAP Feature Importance Plot for flaubert_small_cased ---

ANALYSIS:

Top Predictive Dimensions: Dim 250, Dim 121, and Dim 390 show the highest SHAP values, meaning they strongly influence the model's gender prediction.

Direction of Gender Influence: In Dim 250 and Dim 390, red (high values) tends to push predictions to the right (masculine), while blue (low values) pushes left (feminine).This directional trend is consistent across multiple top dimensions.

Adjective Gender Is Encoded in Specific Dimensions:

The SHAP values are not uniformly distributed only a small subset of dimensions drives the model's decision.This supports the hypothesis that gender is localized in specific regions of the embedding space.

Sharp Impact Transitions: Some dimensions (like Dim 7, Dim 432) show strong split patterns suggesting binary-like thresholds, helpful for classification.

12. Shared Patterns in Noun vs. Adjective SHAP Plots (Flaubert-Small-Cased)

Similar Top Dimensions: Dim 250, Dim 390, Dim 162 appear in the top-ranking features for both nouns and adjectives.This suggests these dimensions consistently carry strong gender signals, regardless of the word type.Indicates shared encoding mechanisms in the embeddings for gender features.

Compact Feature Usage: Both plots confirm that the model relies on a small number of dimensions to predict gender.Supports the hypothesis that gender is localized and not spread across the full embedding space (512 dims).

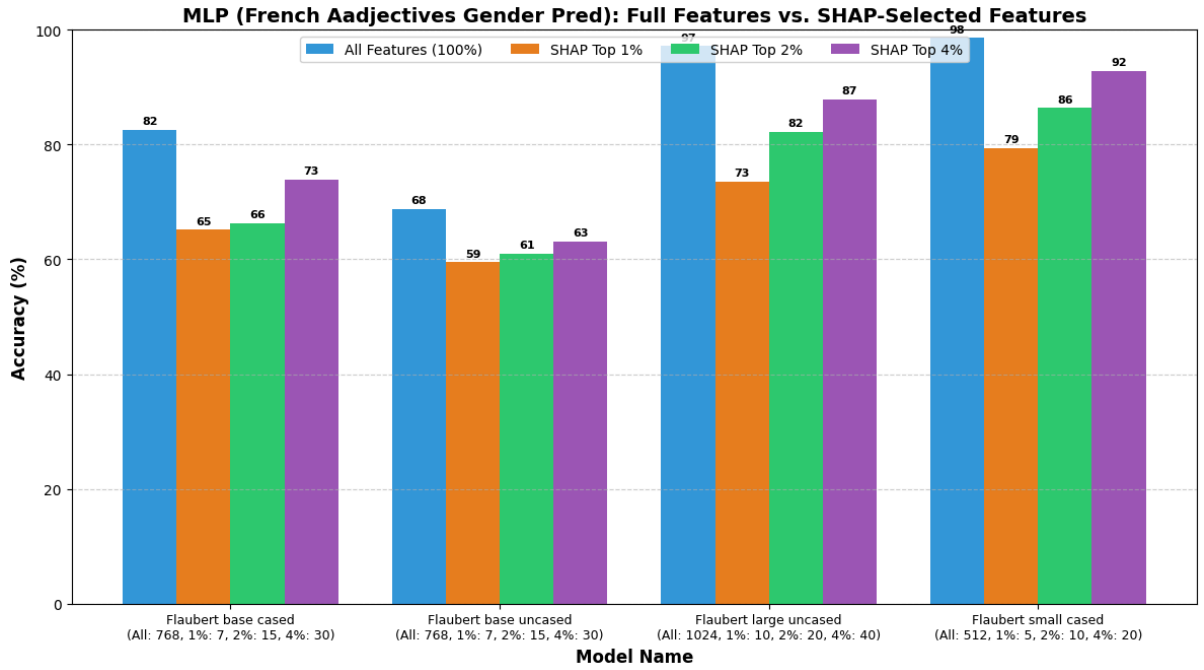
Directional Influence: In both, high SHAP values for red dots (high feature value) push predictions toward masculine.Low values (blue) tend to pull the output toward feminine predictions.

NEXT STEPS:

-> Saving SHAP Feature Importance Results.

-> Retrain Using Selected SHAP Dimensions(1,2,4).

-> Compare Performance of Baseline MLP vs SHAP %N High Importance Features.



ANALYSIS:

Flaubert-small-cased: Accuracy: 98% (all features) → 92% (top 4%) → only 6% drop

- SHAP successfully identifies compact subsets that retain most performance.

Flaubert-large-uncased: Also retains strong accuracy: 97% → 87% (top 4%).

Flaubert-base-cased: Drops from 82% → 73% using top 4%.

Flaubert-base-uncased: Falls from 68% → 63% using top 4%.

13. Comparison between Nouns and Adjectives gender prediction using SHAP-selected features:

-> Adjectives consistently achieve higher accuracy than nouns across all models.

Flaubert-small-cased:

Nouns: 96% (full) → 83% (top 4%)

Adjectives: 98% (full) → 92% (top 4%)

->Both show a drop in performance with very few features (1%), but adjectives recover better at 2–4%.

Flaubert-large-uncased (Adjectives): 97% → 87% (top 4%)

Same model (Nouns): 94% → 83%

->Flaubert-base models show larger performance drops with reduced features.Suggests gender is more diffusely encoded in these models for both nouns and adjectives.

14. Conclusion:

Across both noun and adjective gender prediction , our experiments validate the hypothesis that gender is encoded in a small, meaningful subset of embedding dimensions. The use of a more powerful classifier MLP, trained on 100% of the data enabled SHAP to identify compact feature subsets (as low as 4%) without major drops in performance.

This contrasts with the Perceptron + SHAP setting, where broader feature sets (10–30%) were required to maintain similar accuracy, highlighting that MLP captures complex interactions that Perceptron cannot. Notably, models like flaubert_small_cased performed exceptionally on both tasks (95.7% nouns, 98.6% adjectives), suggesting that some models encode gender more densely and consistently. SHAP consistently selected overlapping dimensions across nouns and adjectives for such models, reinforcing their robust and interpretable internal structure.

In short, MLP + SHAP proves to be a powerful combination for interpretable, compact, and high-performing gender classification in multilingual embeddings.