



# User Aesthetics Identification for Fashion Recommendations

Liwei Liu, Ivo Silva, Pedro Nogueira, Ana  
Magalhães, Eder Martins



FARFETCH



# AGENDA

1. Aesthetics
2. Models & Features
3. Experiments
4. Conclusions & Final Remarks



## AESTHETICS

# Challenges on fashion recommendation

- Unique sense of style
- Personalize the experience
- Incorporate the concepts of fashion and style in our recommenders
- Inspire our customers



# Aesthetic concepts

- Defined by our fashion experts
  - Reflect our customer's style and preferences
- Having a dedicated listing page
  - Curated list of products



# Aesthetic concepts

- Female
  - Arty
  - Classic
  - Edgy
  - Feminine
  - Minimal
  - Streetwear

The screenshot shows the FARFETCH website interface. At the top, there's a navigation bar with a US flag, 'Women', 'Men', and 'Kids' categories. The FARFETCH logo is prominently displayed. To the right, there are icons for user profile, wishlists (2 items), and a shopping bag. Below the navigation, there are links for 'New In', 'Shop By', 'Designers', 'Clothing', 'Shoes', 'Bags', 'Accessories', 'Jewelry', 'Pre-Owned', and 'Sale'. A search bar is also present.

The main content area is titled 'STREET' and includes a sub-header: 'Streetwear - it's the pieces you wear every day. Shop the sports-inspired styles that feel ... [More](#)'. Below this, it indicates '150+ pieces' and a 'Sort by' dropdown menu.

A sidebar on the left contains filters for 'Category', 'Designer', 'Colour', 'Price', 'Same Day Delivery To', and 'Sustainability', each with a downward arrow.

Three product listings are shown, each with a star icon for favoriting:

- Off-White** cropped varsity bomber jacket (New Season)
- Angel Chen** dragon teeth low top sneakers (New Season)
- AMBUSH** logo-waist flared trousers (New Season)

# Aesthetic concepts

- Expert domain knowledge
- User behavior



**Is it possible to predict  
the aesthetics of our customers?**





## Models & Features

A customer could be interested in more than one aesthetics

Multi label classification problem



# Models

- Random Forest
  - Binary relevance
  - Label powerset
- CNN

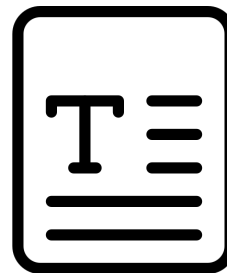
# Features



Statistics



Images

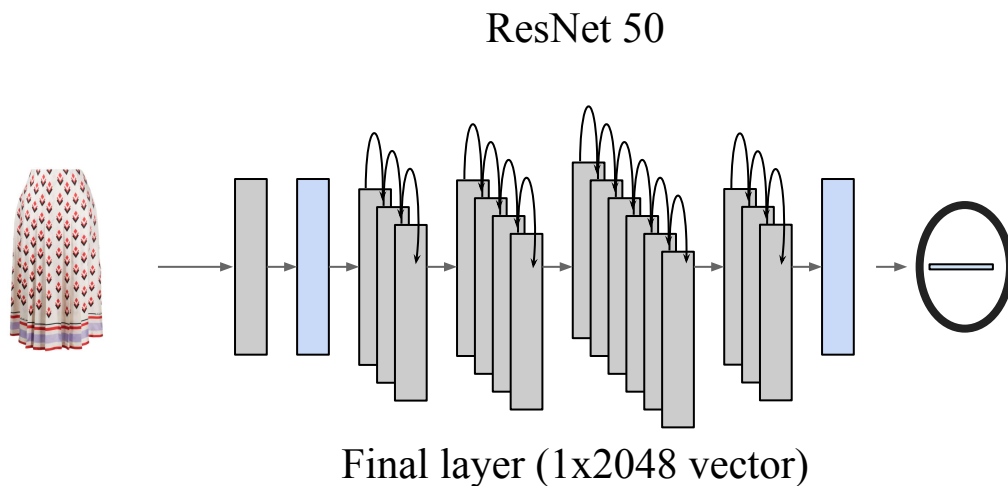


Texts

# User statistics

- Number sessions
  - Number orders
  - ...
  - Customer region
  - Device
  - Categories a user has interacted with
  - Brands a user has interacted with
- } Weighted sum of user actions  
} on those categories and brands

# Image Features



- Avg / min / max their interacted product embeddings
- Cluster all the products embeddings per category

# Textual features

- Tokens/words of all the products a user has interacted with in the training data as features
- TF-IDF
- Word embedding - FastText
  - 1x300 vector

THE DETAILS    SIZE & FIT    SHIPPING & FREE RETURNS

New Season  
**Rejina Pyo**  
Sofia Voile blouse

We can see through you...r Sofia Voile blouse from Rejina Pyo. In a semi-sheer construction, this blouse is style without secrets. Watch your back (because everyone can see it).

Highlights

- blue
- semi-sheer construction
- high neck
- rear zip fastening
- long puff sleeves

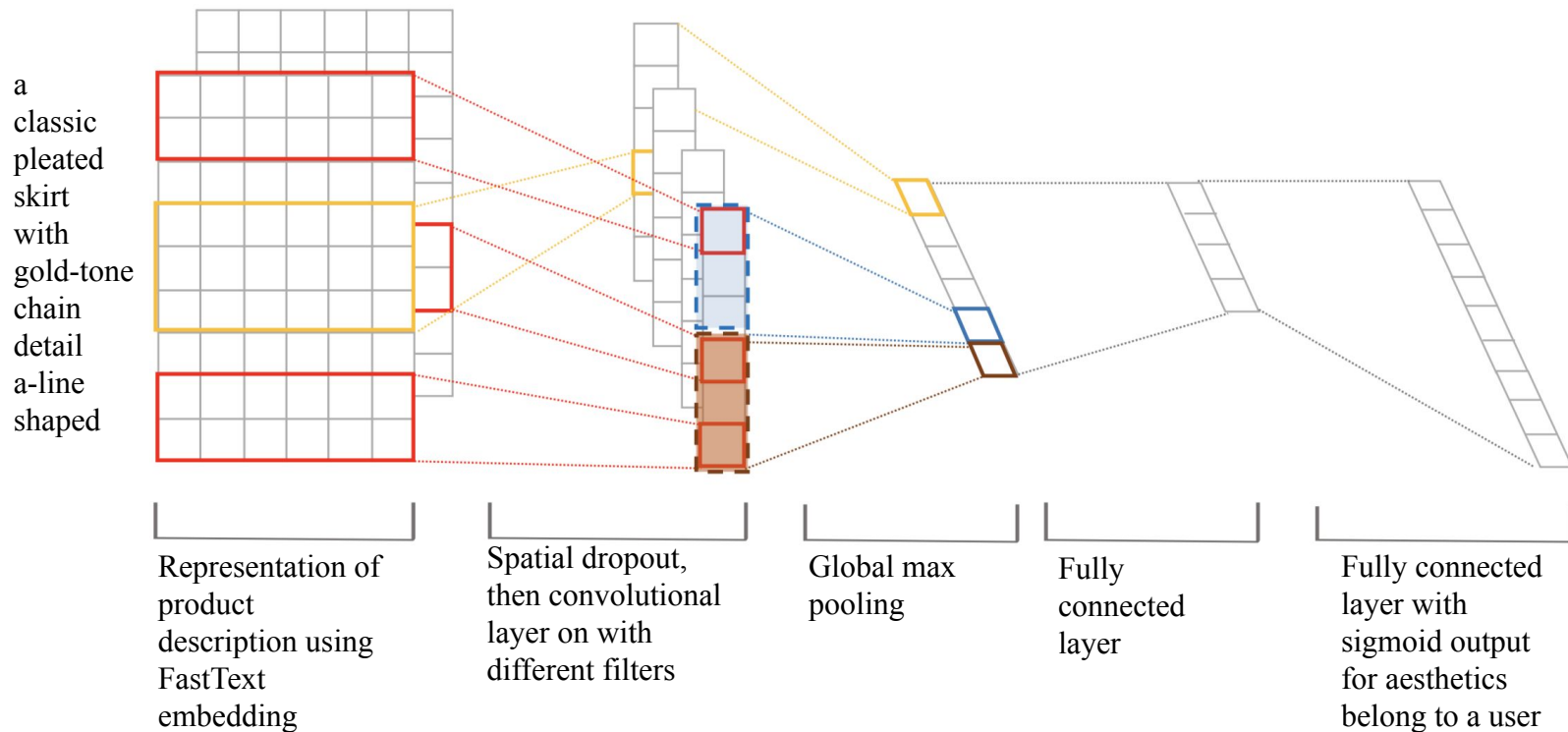
Composition  
Polyamide 50%, Polyester 50%

Washing instructions  
Machine Wash

Designer Style ID: C288VoileBlue

Wearing  
Model is 1.8 m wearing size XS

# CNN with FastText embeddings

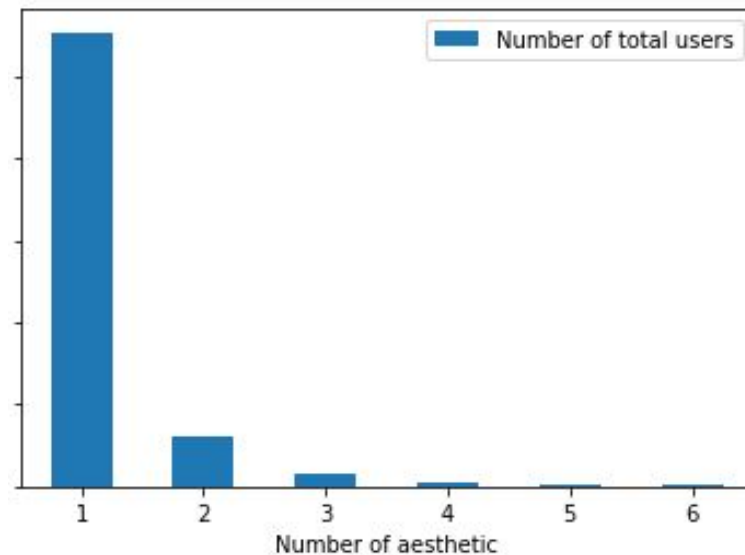
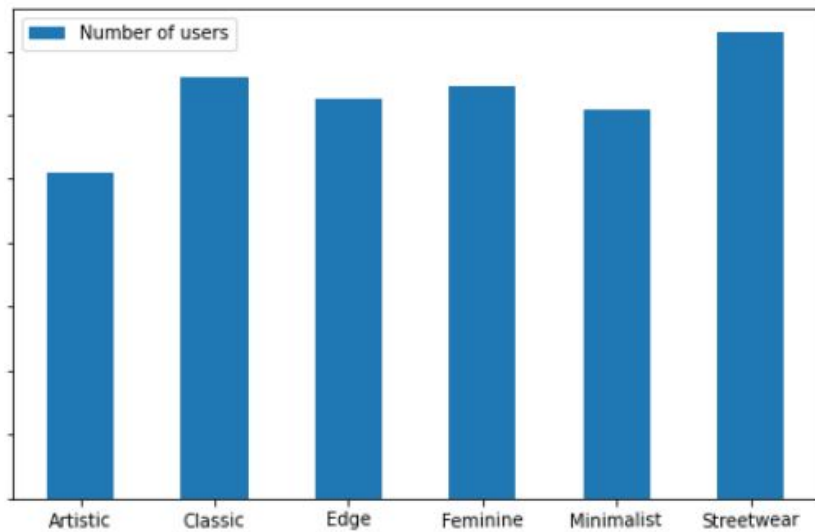




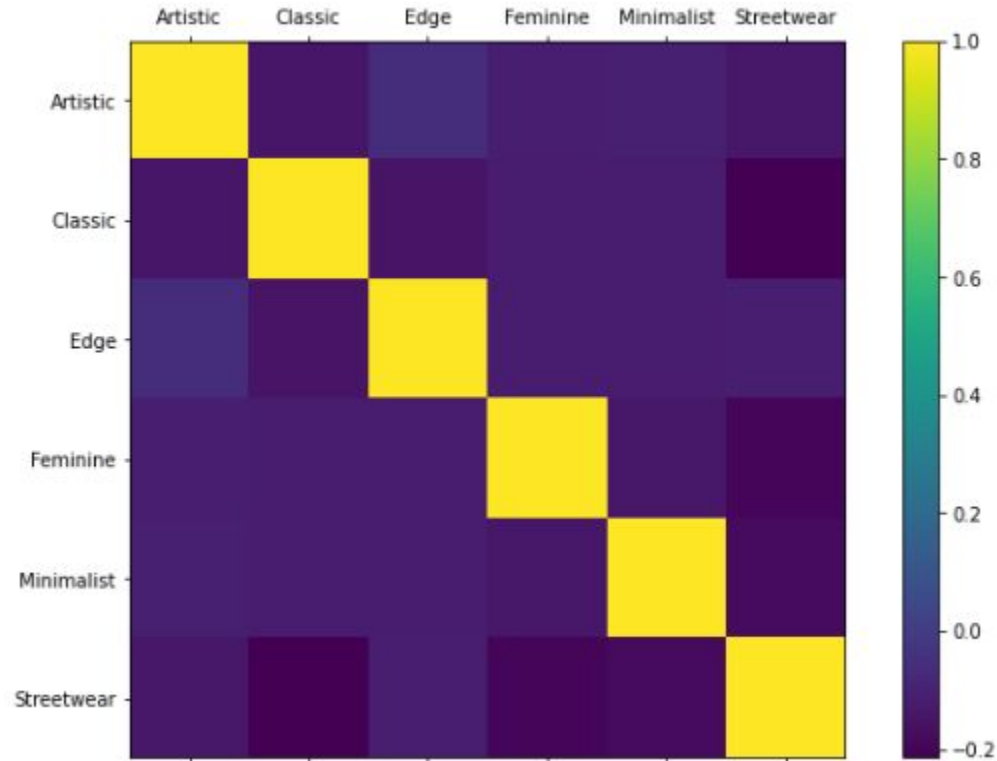


## Experiments

# Fairly balanced



# Aesthetics are not correlated with each other



# Binary Random Forest classification models

Features	F1	Precision	Recall
Word embedding (TF-IDF)	0.525	0.586	0.476
Word embedding (TF-IDF) + Image embedding	0.524	0.585	0.474
General Stats + Word embedding (TF-IDF) + Image embedding	0.507	0.513	0.500
General Stats + Word embedding (TF-IDF)	0.503	0.521	0.486
General Stats	0.442	0.360	0.572
General Stats + Image embedding	0.420	0.382	0.467
Word embeddings (FastText)	0.418	0.335	0.554
Image embedding (clusters)	0.348	0.295	0.424
Random	0.257	0.197	0.370

# Binary Random Forest classification models

	Features	F1	Precision	Recall
Single features	<b>Word embedding (TF-IDF)</b>	<b>0.525</b>	<b>0.586</b>	<b>0.476</b>
	Word embedding (TF-IDF) + Image embedding	0.524	0.585	0.474
	General Stats + Word embedding (TF-IDF) + Image embedding	0.507	0.513	0.500
	General Stats + Word embedding (TF-IDF)	0.503	0.521	0.486
	<b>General Stats</b>	<b>0.442</b>	<b>0.360</b>	<b>0.572</b>
	General Stats + Image embedding	0.420	0.382	0.467
	<b>Word embeddings (FastText)</b>	<b>0.418</b>	<b>0.335</b>	<b>0.554</b>
	<b>Image embedding (clusters)</b>	<b>0.348</b>	<b>0.295</b>	<b>0.424</b>
	Random	0.257	0.197	0.370

# Binary Random Forest classification models

	Features	F1	Precision	Recall
All feature combinations	Word embedding (TF-IDF)	0.525	0.586	0.476
	<b>Word embedding (TF-IDF) + Image embedding</b>	<b>0.524</b>	<b>0.585</b>	<b>0.474</b>
	<b>General Stats + Word embedding (TF-IDF) + Image embedding</b>	<b>0.507</b>	<b>0.513</b>	<b>0.500</b>
	<b>General Stats + Word embedding (TF-IDF)</b>	<b>0.503</b>	<b>0.521</b>	<b>0.486</b>
	General Stats	0.442	0.360	0.572
	<b>General Stats + Image embedding</b>	<b>0.420</b>	<b>0.382</b>	<b>0.467</b>
	Word embeddings (FastText)	0.418	0.335	0.554
	Image embedding (clusters)	0.348	0.295	0.424
	Random		0.257	0.197

# Binary Random Forest classification models

Random Forest with Word embedding (TF-IDF) features performs better.

Some words, in product descriptions could be used as a strong indicator of aesthetics preferences.

Features	F1	Precision	Recall
<b>Word embedding (TF-IDF)</b>	<b>0.525</b>	<b>0.586</b>	<b>0.476</b>
Word embedding (TF-IDF) + Image embedding	0.524	0.585	0.474
General Stats + Word embedding (TF-IDF) + Image embedding	0.507	0.513	0.500
General Stats + Word embedding (TF-IDF)	0.503	0.521	0.486
General Stats	0.442	0.360	0.572
General Stats + Image embedding	0.420	0.382	0.467
Word embeddings (FastText)	0.418	0.335	0.554
Image embedding (clusters)	0.348	0.295	0.424
Random	0.257	0.197	0.370

# Binary Random Forest classification models

Features	F1	Precision	Recall
Word embedding (TF-IDF)	0.525	0.586	0.476
Word embedding (TF-IDF) + Image embedding	0.524	0.585	0.474
General Stats + Word embedding (TF-IDF) + Image embedding	0.507	0.513	0.500
General Stats + Word embedding (TF-IDF)	0.503	0.521	0.486
General Stats	0.442	0.360	0.572
General Stats + Image embedding	0.420	0.382	0.467
Word embeddings (FastText)	0.418	0.335	0.554
<b>Image embedding (clusters)</b>	<b>0.348</b>	<b>0.295</b>	<b>0.424</b>
Random	0.257	0.197	0.370

Image embedding perform the worst.

In the same aesthetic products could look very different, resulting in very different embeddings, which in turn confuses Random Forest.



# Random Forest vs CNN

Time range	Algorithm	Features	F1	Precision	Recall
6 months	RF	Word embedding (TF-IDF)	0.525	0.586	0.476
3 months	RF	Word embedding (TF-IDF)	0.505	0.555	0.463
6 months	CNN	Word embedding (FastText)	0.404	0.680	0.288
3 months	CNN	Word embedding (FastText)	0.307	0.687	0.199

# Random Forest vs CNN

The addition of data have little impact on the model quality

Time range	Algorithm	Features	F1	Precision	Recall
<b>6 months</b>	<b>RF</b>	<b>Word embedding (TF-IDF)</b>	<b>0.525</b>	<b>0.586</b>	<b>0.476</b>
<b>3 months</b>	<b>RF</b>	<b>Word embedding (TF-IDF)</b>	<b>0.505</b>	<b>0.555</b>	<b>0.463</b>
6 months	CNN	Word embedding (FastText)	0.404	0.680	0.288
3 months	CNN	Word embedding (FastText)	0.307	0.687	0.199

# Random Forest vs CNN

CNN model have a significant increase in recall.

Time range	Algorithm	Features	F1	Precision	Recall
6 months	RF	Word embedding (TF-IDF)	0.525	0.586	0.476
3 months	RF	Word embedding (TF-IDF)	0.505	0.555	0.463
<b>6 months</b>	<b>CNN</b>	<b>Word embedding (FastText)</b>	<b>0.404</b>	<b>0.680</b>	<b>0.288</b>
<b>3 months</b>	<b>CNN</b>	<b>Word embedding (FastText)</b>	<b>0.307</b>	<b>0.687</b>	<b>0.199</b>

# Random Forest vs CNN

CNN models performed better on precision at the cost of recall leading to a worst F1 when compared with Random Forest.

Time range	Algorithm	Features	F1	Precision	Recall
6 months	RF	Word embedding (TF-IDF)	0.525	0.586	<b>0.476</b>
3 months	RF	Word embedding (TF-IDF)	0.505	0.555	<b>0.463</b>
6 months	CNN	Word embedding (FastText)	0.404	<b>0.680</b>	0.288
3 months	CNN	Word embedding (FastText)	0.307	<b>0.687</b>	0.199

# Aesthetics results breakdown

Note the positive correlation between class frequency and the evaluation metrics which might be an indicator that more popular aesthetics are easier to classify.

Aesthetic	Frequency	F1	Precision	Recall
Streetwear	<b>0.230</b>	<b>0.635</b>	0.739	0.557
Classic	<b>0.207</b>	<b>0.589</b>	0.671	0.524
Feminine	<b>0.203</b>	<b>0.483</b>	0.554	0.428
Edge	<b>0.196</b>	<b>0.484</b>	0.551	0.431
Minimalist	<b>0.192</b>	<b>0.499</b>	0.583	0.437
Artistic	<b>0.158</b>	<b>0.442</b>	0.525	0.383

# Feminine Aesthetic customer example



cow neck tank mini dress  
**Maisie Wilen**



puff sleeve midi dress  
**CECILIE BAHNSEN**



Livarno satin midi skirt  
**GAUGE81**



June v-neck camisole  
**BERNADETTE**



Kim high neck top  
**ROTATE**



## Final Remarks

- Aesthetics could be inferred from our customer shopping behavior
- Future work
  - Test in live
  - Conduct a survey study to improve and validate our models

