

AUTOMATIC PRODUCT CLASSIFICATION

Project



Automatically classify
consumer goods based on
product description and image

Challenges

- Avoid manual attribution of the category
- Improve user experience
- Prepare for the future scaling up

MISSION



Create a Proof of Concept of the unsupervised classification based on product description and image



Perform a supervised product classification based on image

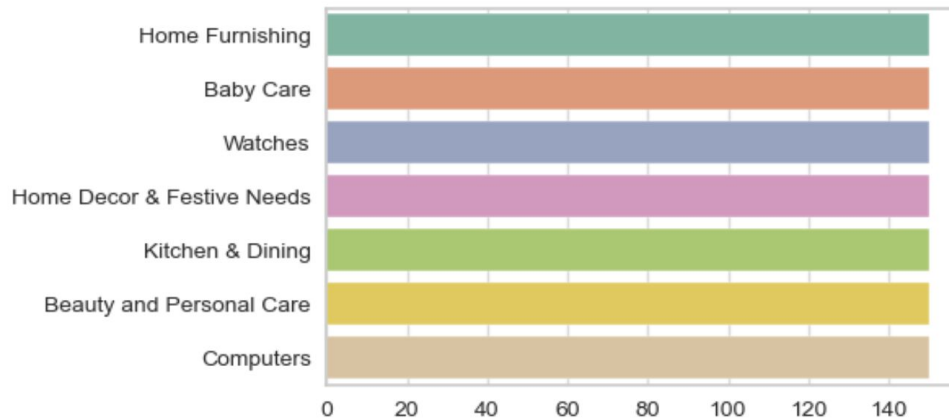


Test product extraction from an API

DATA

Quick overview

- 1050 products
- 15 features
- 1050 image files
- 2% null values
- 7 main categories
- 150 items per category
- free of intellectual property issues



FEATURE ENGINEERING

FEATURE	INITIAL	TRANSFORMATION
CATEGORY	`product_category_tree`	<ul style="list-style-type: none">- Extract first level category name- Encode with LabelEncoder
DESCRIPTION	`product_name` `description`	Merge `product_name` and `description` fields
IMAGE	`image`	Extract grayscale matrix from the image file

DESCRIPTION BASED UNSUPERVISED CLASSIFICATION

TEXT PREPROCESSING

01



TECHNICAL

- lowercase
- remove stop-words
- remove punctuation
- keep alpha characters
- lemmatize
- remove 1 letter tokens

02



SEMANTIC

- remove the most frequent generic tokens
- remove rare tokens (< 3 times)

FEATURE EXTRACTION & CLASSIFICATION PROCESS

Bag of Words and
Word embeddings

VECTORIZATION



STEP 1

STEP 2



DIMENSIONALITY
REDUCTION

PCA & T-SNE to reduce
to 2 features

Plot with true
categories

GRAPHIC ANALYSIS



STEP 3

STEP 4

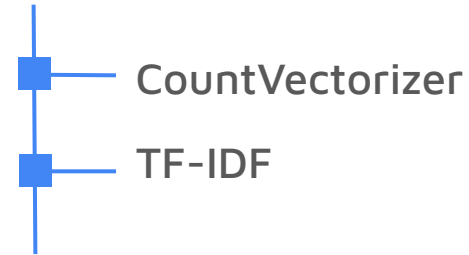


EVALUATION

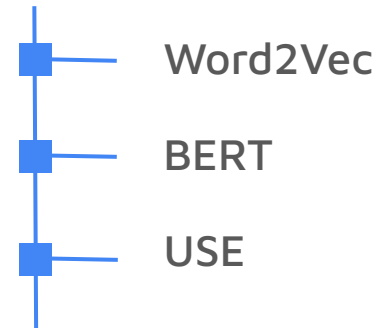
K-Means clustering
and ARI score

FEATURE EXTRACTION APPROACHES

BAG OF WORDS

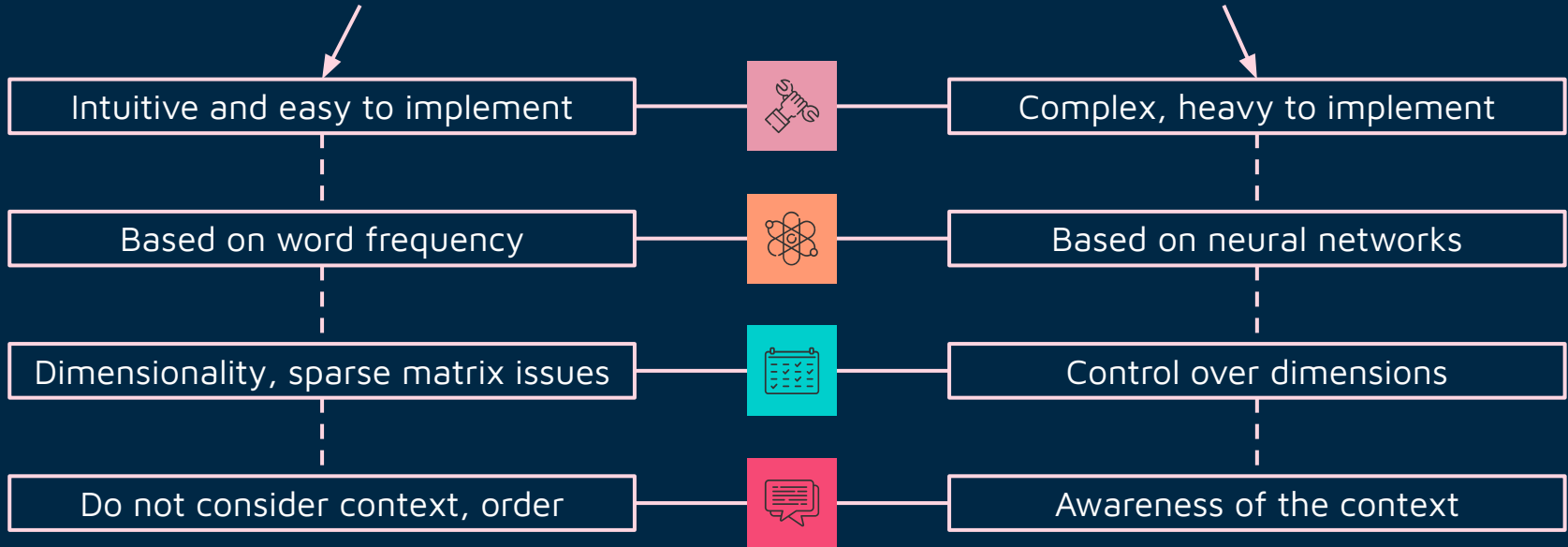


WORD EMBEDDINGS

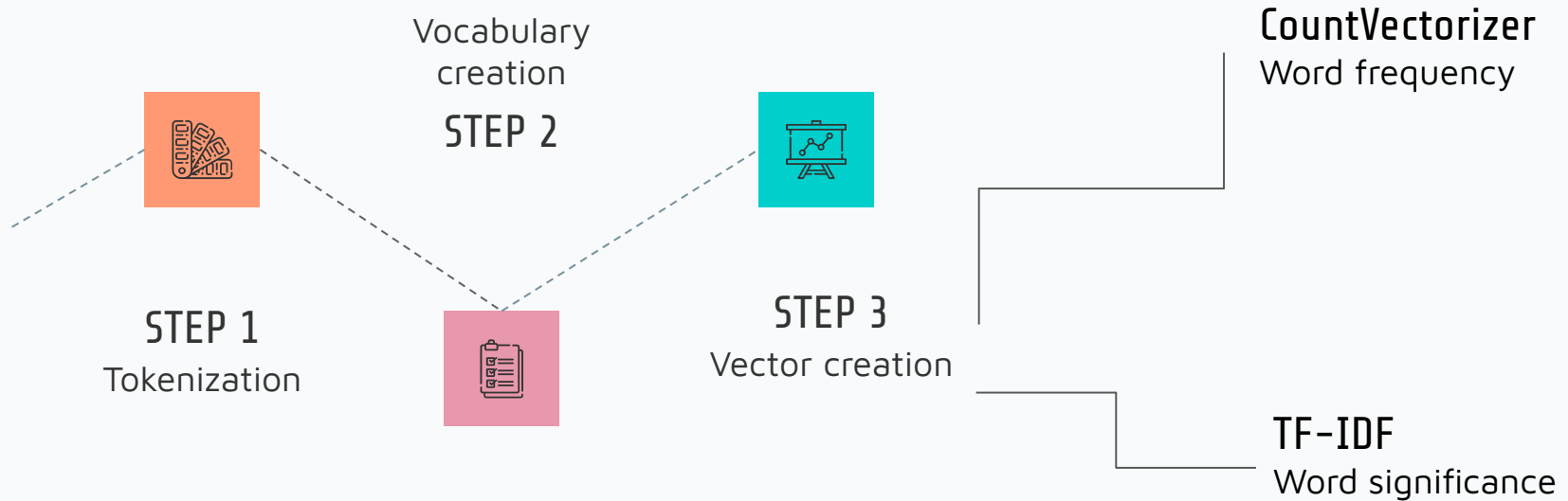


Bag Of Words

Word Embeddings

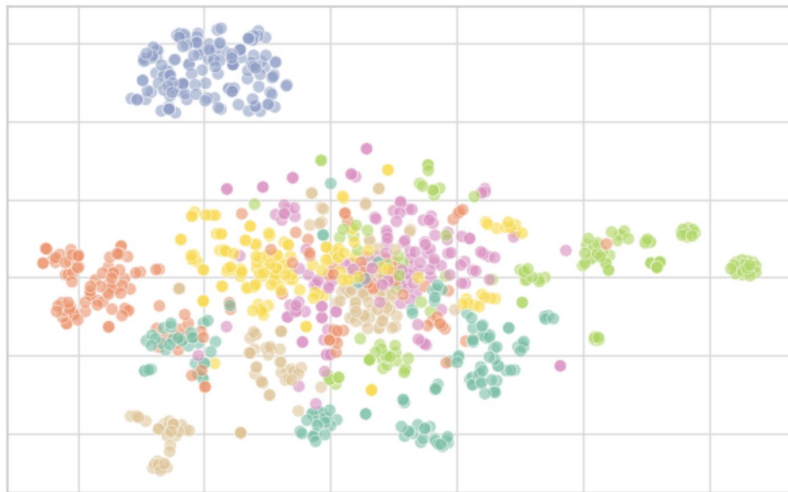


BAG OF WORDS



BAG OF WORDS results

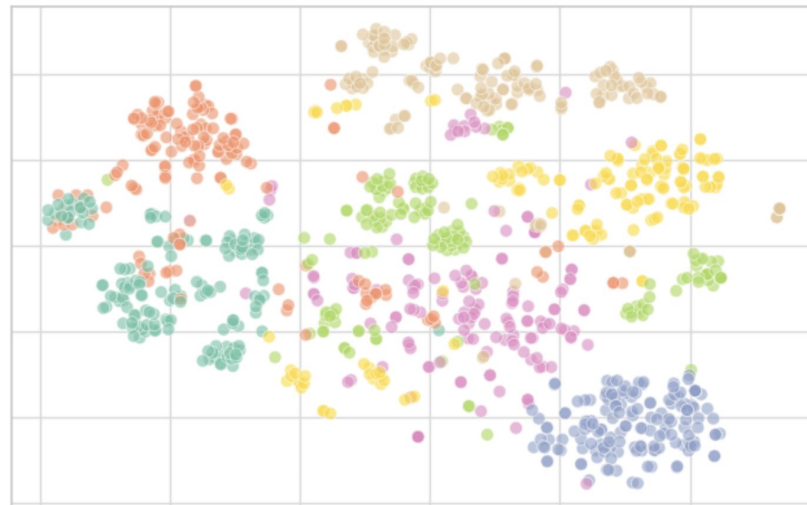
CountVectorizer



ARI: 0.39

execution time: 0.03 sec

TF-IDF



ARI: 0.51

execution time: 0.03 sec

WORD EMBEDDINGS

Word2Vec	BERT	USE
<ul style="list-style-type: none">• Simple single layered neural network• Word embedding model• Single vector per word• Trained on the given corpus	<ul style="list-style-type: none">• 12 layer deep neural network• Transformer-based architecture• Language representation model (word + sentence)• Context-based different vectors per word• Different pre-trained models available	<ul style="list-style-type: none">• Transformer-based or Deep Averaging Network• Sentence embedding model• Trained on Wikipedia and web content
~ 8 sec	~ 233 sec	< 1 sec
0.45 score	0.31 score	0.66 score

KEY POINTS

TF-IDF (0.51)

- Simple, efficient, performant
- Can be improved by using n-grams, tuning parameters
- Sparse matrix that will get larger

USE (0.66)

- Straightforward to implement
- Pre-trained model that is well suited for our dataset

IMAGE BASED UNSUPERVISED CLASSIFICATION

IMAGES

Home Furnishing



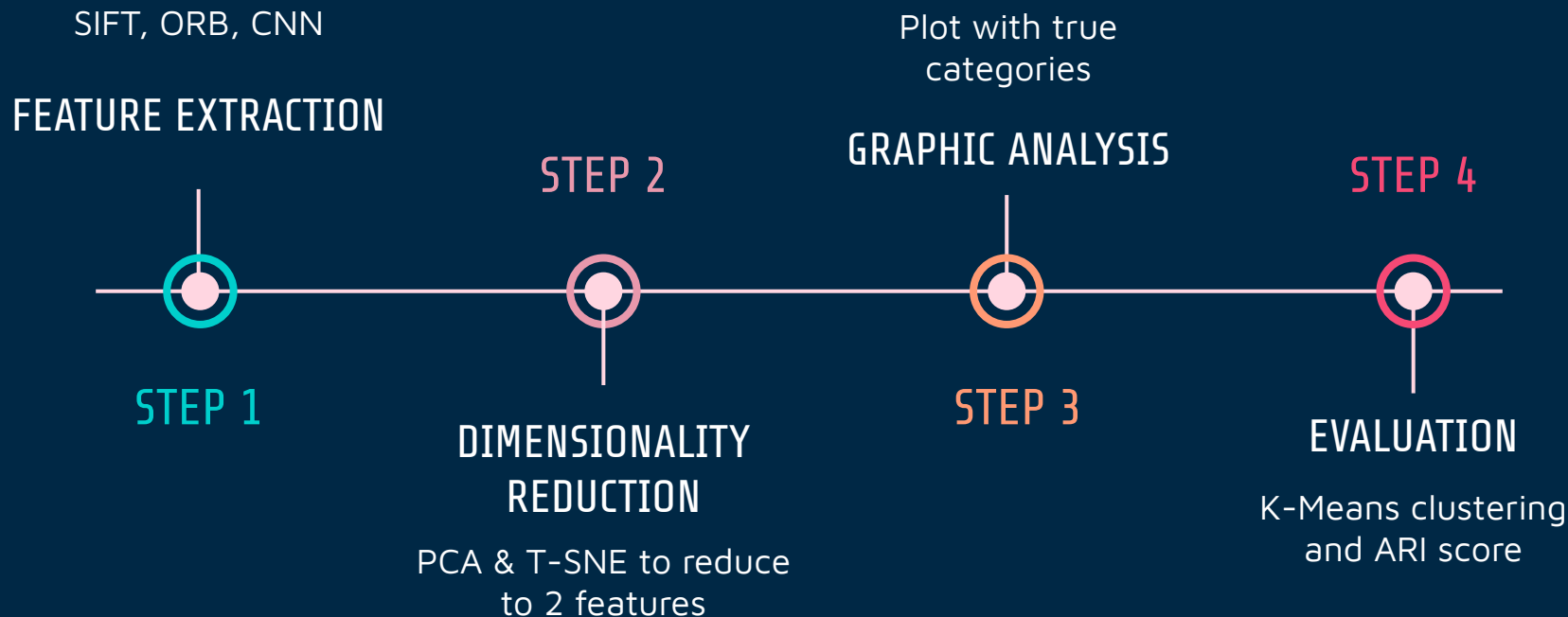
Kitchen & Dining



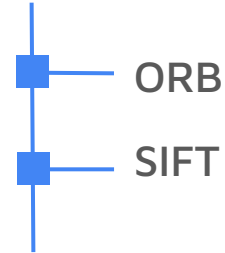
Watches



FEATURE EXTRACTION & CLASSIFICATION PROCESS



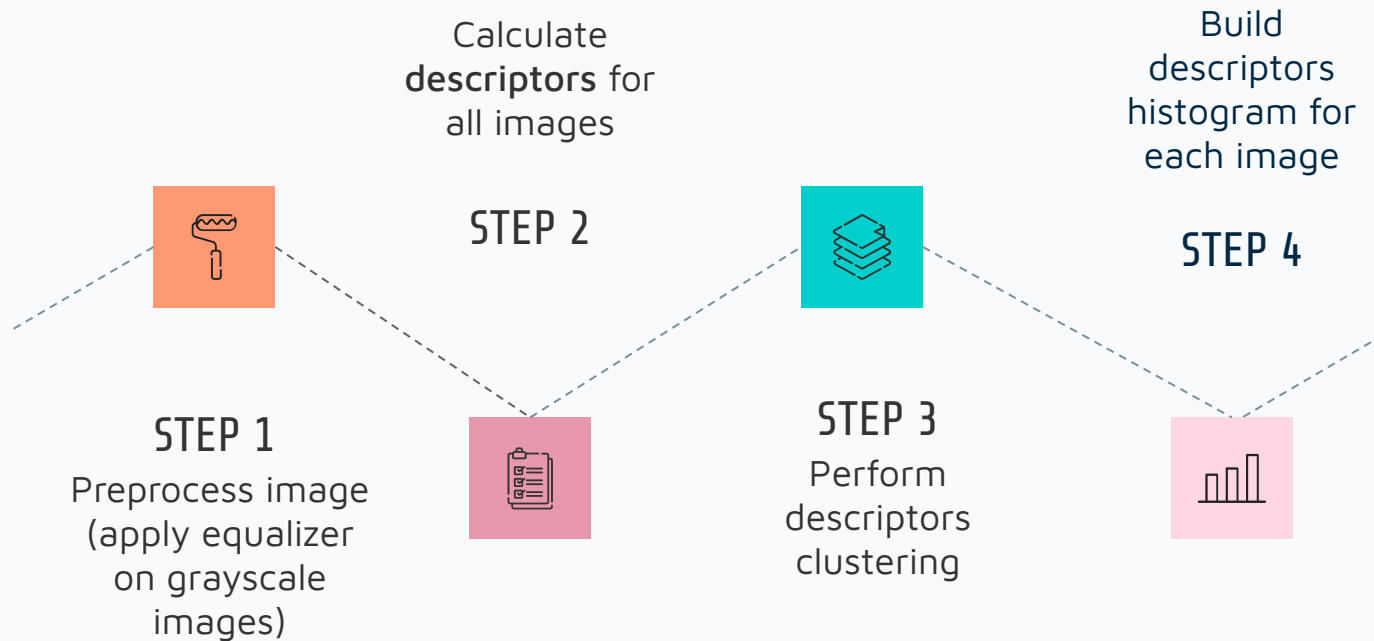
FEATURE EXTRACTION APPROACHES



Convolutional Neural Networks



ORB & SIFT FEATURE EXTRACTION



KEYPOINTS & DESCRIPTORS DETECTION

Image features should be:

- Repeatable (robust to scale, rotation, noise, etc)
- Distinctive
- Local

ORB



~ 24 sec

0.035 score

SIFT

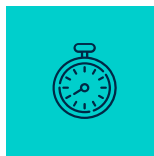


~ 177 sec

0.045 score

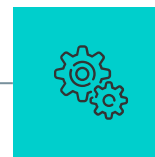
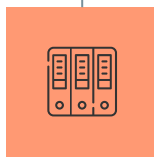
TRANSFER LEARNING: BENEFITS

TIME
Saving training time



PERFORMANCE
Better performance
of neural networks

SMALL DATA
Not needing a lot of
data



ML XP
Easy to implement
and customize

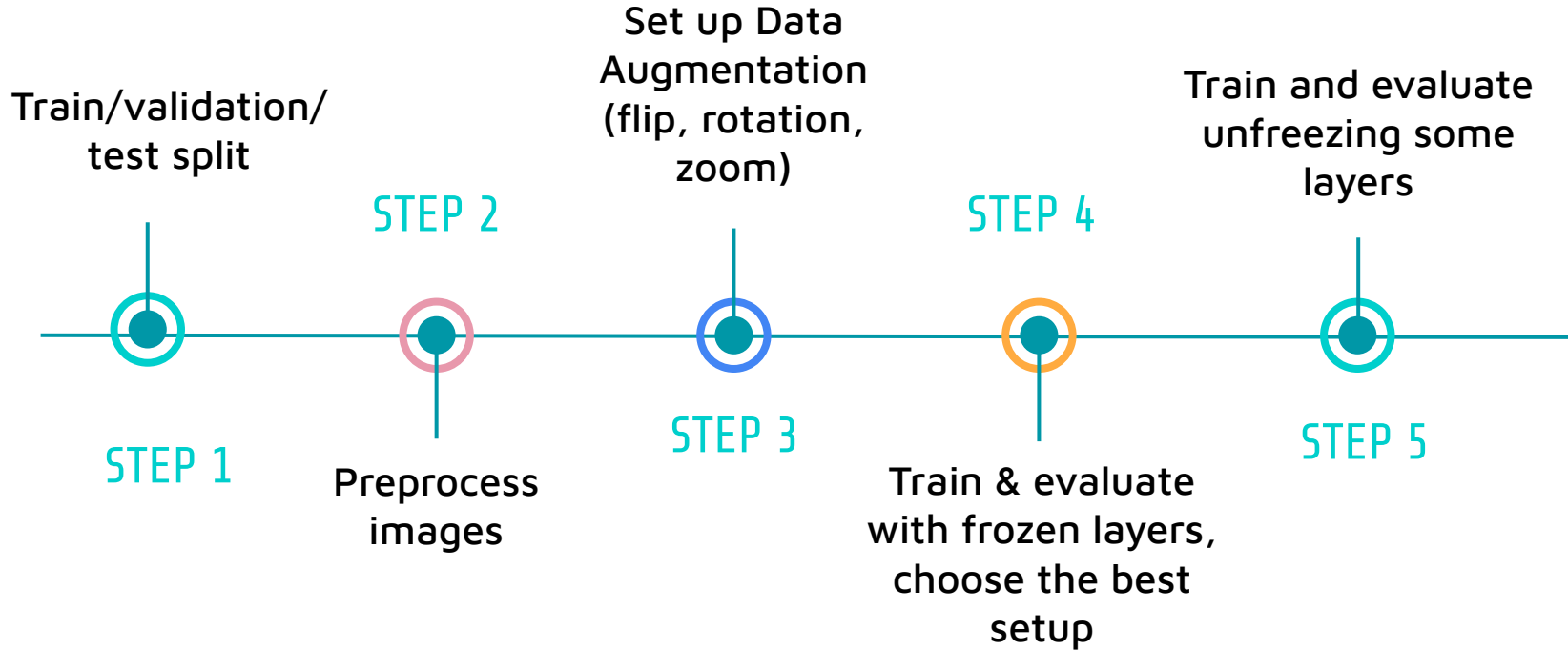


FEATURE EXTRACTION WITH CNN

VGG16	ResNet50
<ul style="list-style-type: none">• 16 layers• trained on Imagenet• big model size due to its depth and the number of fully-connected nodes	<ul style="list-style-type: none">• 50 layers• trained on Imagenet• smaller model size due to the usage of global average pooling
~ 99 sec	~ 65 sec
0.43 score	0.55 score

IMAGE-BASED SUPERVISED CLASSIFICATION

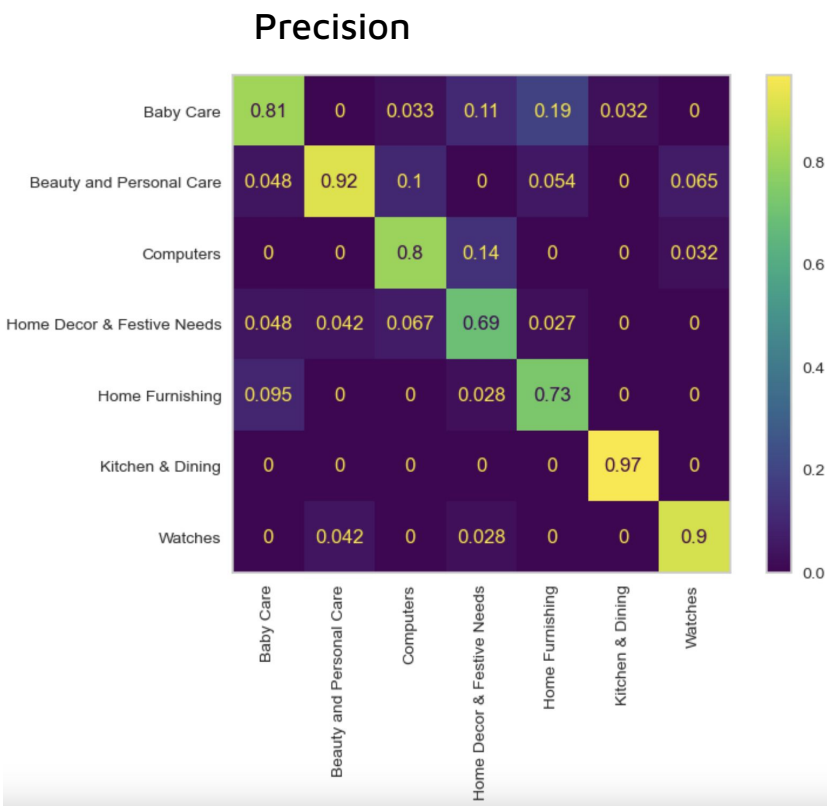
CLASSIFICATION WITH RESNET50 MODEL WORKFLOW



TESTED MODEL SETUPS

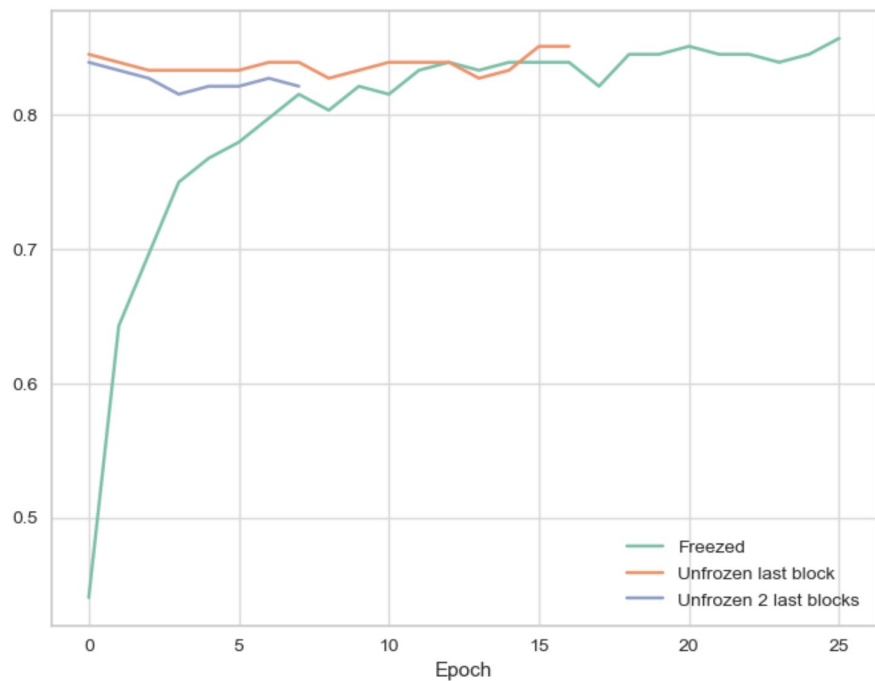
Dense layer 256 nodes	2 dense layers	Dense layer 512 nodes
Data augmentation -> Base ResNet50 model -> Global Average Pooling		
Dense layer 256 nodes ('relu') Dropout (0.5)	Dense layer 256 nodes ('relu') Dropout (0.2) Dense layer 128 nodes ('relu') Dropout (0.5)	Dense layer 512 nodes ('relu') Dropout (0.5)
Dense layer 7 nodes ('softmax')		
val accuracy: 0.84 val loss: 0.57 test accuracy: 0.81 test loss: 0.6	val accuracy: 0.85 val loss: 0.51 test accuracy: 0.82 test loss: 0.6	val accuracy: 0.83 val loss: 0.57 test accuracy: 0.81 test loss: 0.59

EVALUATION

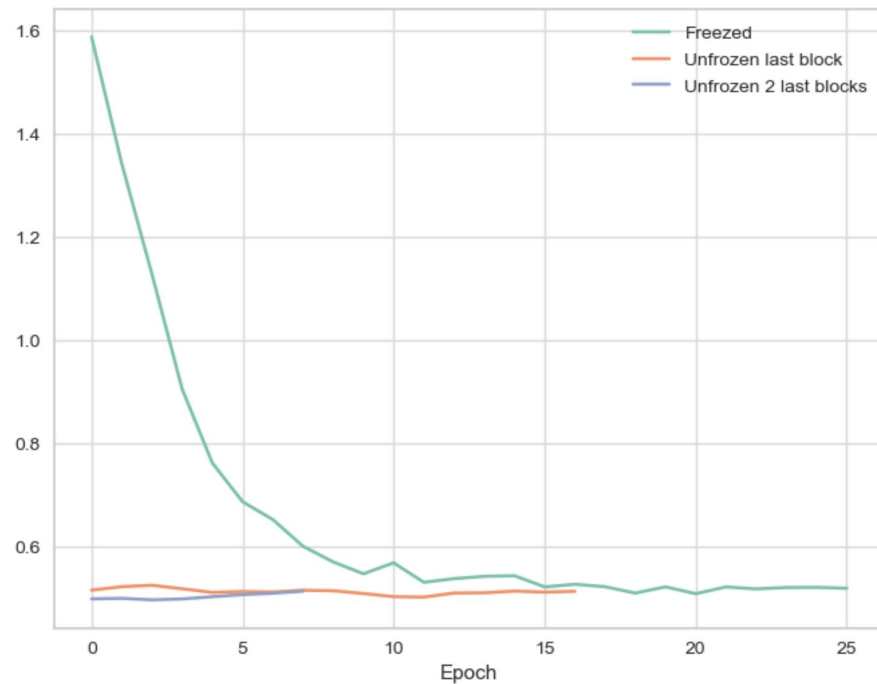


FINE-TUNING

Validation accuracy



Validation loss



DATA EXTRACTION FROM AN API

API INFORMATION

DATA SOURCE	Edamam
DATA PROVIDER	RapidApi
ENDPOINT	/api/food-database/v2/parser
QUERY	{"ingr": "champagne"}

EXTRACTED DATA

	foodId	label	category	foodContentsLabel	image
0	food_a656mk2a5dmqb2adiamu6beihduu	Champagne	Generic foods	NaN	https://www.edamam.com/food-img/a71/a718cf3c52...
1	food_b753ithamdb8psbt0w2k9aquo06c	Champagne Vinaigrette, Champagne	Packaged foods	OLIVE OIL; BALSAMIC VINEGAR; CHAMPAGNE VINEGAR...	NaN
2	food_b3dyababjo54xobm6r8jzbghjqqe	Champagne Vinaigrette, Champagne	Packaged foods	INGREDIENTS: WATER; CANOLA OIL; CHAMPAGNE VINE...	https://www.edamam.com/food-img/d88/d88b64d973...
3	food_a9e0ghsamvoc45bwa2ybsa3gken9	Champagne Vinaigrette, Champagne	Packaged foods	CANOLA AND SOYBEAN OIL; WHITE WINE (CONTAINS S...	NaN
4	food_an4jjueaucpus2a3u1ni8auhe7q9	Champagne Vinaigrette, Champagne	Packaged foods	WATER; CANOLA AND SOYBEAN OIL; WHITE WINE (CON...	NaN
5	food_bmu5dmkazwuvpaa5prh1daa8jxs0	Champagne Dressing, Champagne	Packaged foods	SOYBEAN OIL; WHITE WINE (PRESERVED WITH SULFIT...	https://www.edamam.com/food-img/ab2/ab2459fc2a...
6	food_alpl44taoyv11ra0lic1qa8xculi	Champagne Buttercream	Generic meals	sugar; butter; shortening; vanilla; champagne;...	NaN
7	food_byap67hab6evc3a0f9w1oag3s0qf	Champagne Sorbet	Generic meals	Sugar; Lemon juice; brandy; Champagne; Peach	NaN
8	food_am5egz6aq3fpjlaf8xpkcdbc2asis	Champagne Truffles	Generic meals	butter; cocoa; sweetened condensed milk; vanil...	NaN
9	food_bcz8rhiajk1fuva0vkfmeakbouc0	Champagne Vinaigrette	Generic meals	champagne vinegar; olive oil; Dijon mustard; s...	NaN

GDPR COMPLIANCE

1

PURPOSE LIMITATION

The data must be processed only for the given purpose

2

DATA RELEVANCE

Gather only the necessary data

3

STORAGE LIMITATIONS

The data must not be stored longer than intended

4

INTEGRITY,
CONFIDENTIALITY

The data must be processed only by the people who have access to it

5

LAWFULNESS, FAIRNESS,
TRANSPARENCY

Valid legal basis, best person's interest, clear communication

TO GO FURTHER

- Continue customizing Data Augmentation techniques
- Train on text and image features together
- Try out other network architectures or different models
- Change the target from the main category to a subcategory

THANKS!

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