Shopee Product Matching

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Agenda

1. Problem Statement
2. Exploratory Data Analysis
3. Image Embedding
4. Text Embedding
5. Combined Predictions
6. Conclusions and Recommendations

1. Problem Statement

Goal

- To provide competitive prices to customers, retail companies like Shopee use product matching to **identify identical products** on their platform
- Given a list of product images and titles, **predict which products are the same**

Prediction Format

If [A, B, C, D, E] is the set of all unique products and we predict [A, B, C] to be the same and [D, E] to be the same:

Product	Prediction
A	A, B, C
B	B, A, C
C	C, A, B
D	D, E
E	E, D

Scoring Metric

Predictions will be scored row-wise then averaged using F1 score / Dice Metric:

$$\frac{2 * |X \cap Y|}{|X| + |Y|}$$

where X is the set of our predictions and Y is the set of actual matches

Scoring Metric

If [A, B] and [C, D, E] are the actual matching sets:

Product	Prediction	Actual Matches	F1 Score
A	A, B, C	A, B	0.8
B	B, A, C	B, A	0.8
C	C, A, B	C, D, E	0.33
D	D, E	D, C, E	0.8
E	E, D	E, C, D	0.8
		Average Score	**0.71**

Approach

- Generate image feature embeddings
- Generate text feature embeddings
- Search embedding space for nearest neighbours
- Combine image and text predictions

Challenges

- Precision vs recall
- Noisy data
- Combining image and text predictions

2. Exploratory Data Analysis

Train

34,250

rows

5

columns:

- posting_id
- image
- image_phash
- title
- label_group

Test

70,000+

rows

4

columns:

- posting_id
- image
- image_phash
- title

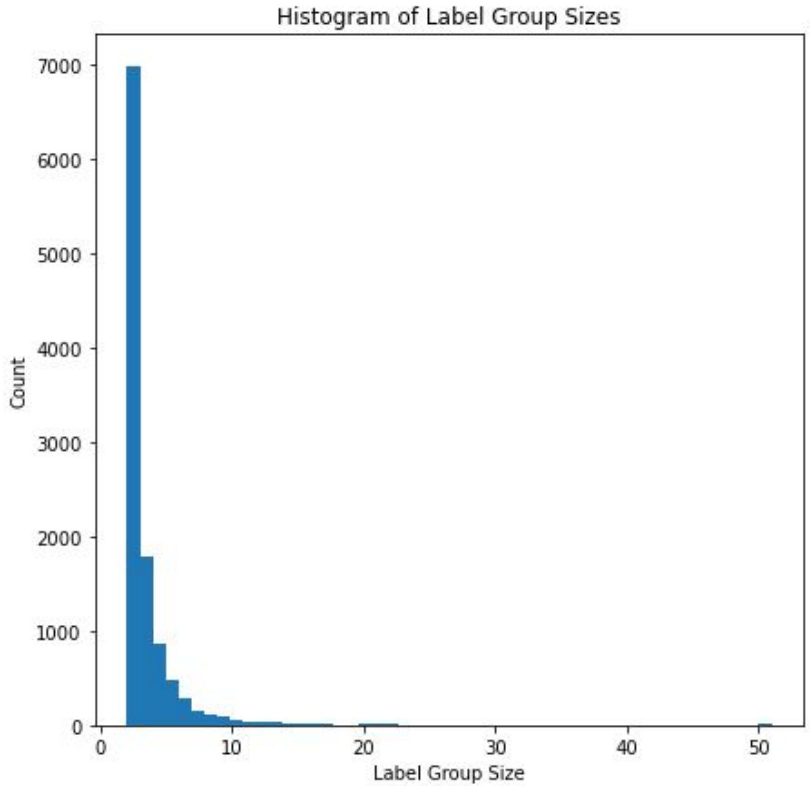
Data Dictionary

posting_id	Unique identification number of a product
image	Image file name
image_phash	Image perceptual hash
title	Product title
label_group	Identification number for actual matches **Products are the same if they have the same label group**

	posting_id	image	image_phash	title	label_group
0	train_129225211	0000a68812bc7e98c42888dfb1c07da0.jpg	94974f937d4c2433	Paper Bag Victoria Secret	249114794
1	train_3386243561	00039780dfc94d01db8676fe789ecd05.jpg	af3f9460c2838f0f	Double Tape 3M VHB 12 mm x 4,5 m ORIGINAL / DO...	2937985045
2	train_2288590299	000a190fdd715a2a36faed16e2c65df7.jpg	b94cb00ed3e50f78	Maling TTS Canned Pork Luncheon Meat 397 gr	2395904891
3	train_2406599165	00117e4fc239b1b641ff08340b429633.jpg	8514fc58eafea283	Daster Batik Lengan pendek - Motif Acak / Camp...	4093212188
4	train_3369186413	00136d1cf4edede0203f32f05f660588.jpg	a6f319f924ad708c	Nescafe \xc3\x89clair Latte 220ml	3648931069

Label Groups

- 11,014 label groups in train data
- Sizes range from 2 to 51
- **63% size 2**, 16% size 3, 8% size 4
- Test data:
  - Sizes range from 2 to 51
  - Unknown number/distribution of label groups



Images

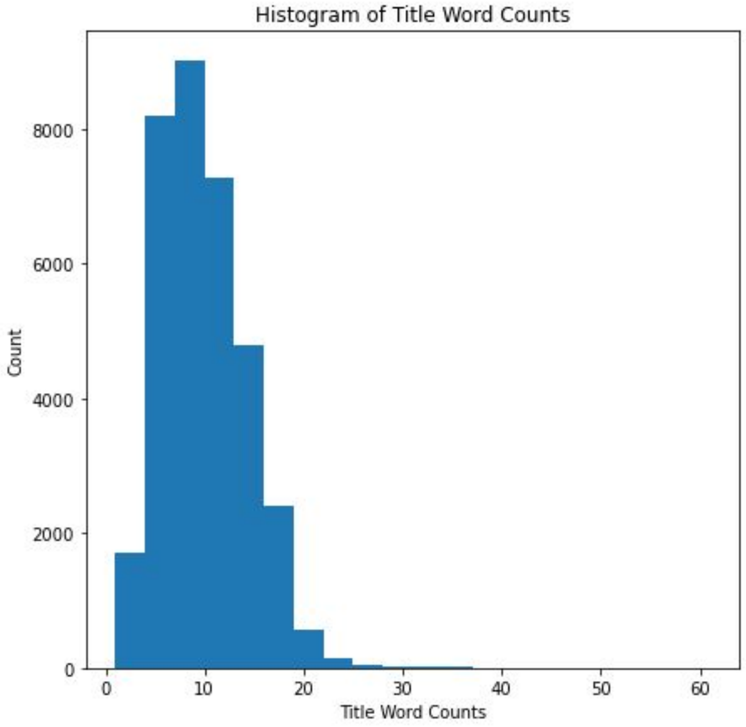
Images differ in:

- Image size
- Image phash
- Overlaying of words/branding
- Positioning/size of the product within the image
- Background colour

Sample images from same label group

Titles

- Titles comprise about 10 words on average
- Top tokens include English/Indonesian words and non-alphanumeric characters



Top title tokens

Token	Count
/	8616
-	5221
anak	1916
wanita	1820
‘‘	1706
original	1681
1	1400
murah	1363
tas	1192
dan	1157

Titles

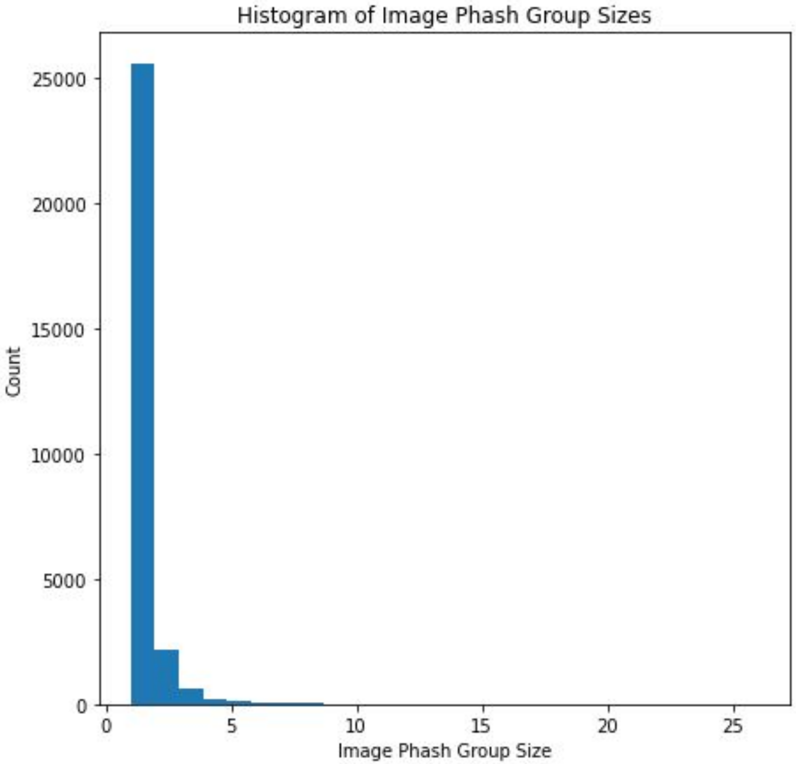
- Mix of English and Indonesian
- Common stop words e.g. 'original', ‘new’, ‘ready’
- Same keywords in same label groups
- Non-alphanumeric, UTF-8 characters e.g. ‘/’, ‘-’, ‘\\xc3’

Sample titles from same label groups

```
SCARLETT SERUM - BEBAS PILIH
SCARLETT WHITENING ACNE SERUM
SERUM SCARLETT ACNE & BRIGHTLY- SERUM WAJAH SCARLETT ORIGINAL BPOM
Scarlett Whitening Brightly Ever After Serum
SCARLETT serum wajah NEW
SERUM SCARLETT ACNE & BRIGHTLY- FACE SERUM ORIGINAL BPOM
SCARLETT Whitening Brightly Ever After Serum / Whitening Acne Serum
SCARLETT WHITENING BRIGHTLY EVER AFTER SERUM
SCARLETT ACNE SERUM & BRIGHTLY EVER AFTER SERUM
Scarlett Serum
SERUM SCARLETT 15ML BRIGHTLY / ACNE PILIH SALAH SATU
SCARLETT ACNE SERUM / BRIGHTLY EVER AFTER SERUM
SCARLETT WHITENING SERUM
[READY] Scarlett Whitening Serum Acne/ Brightly Ever After by felicia
Scarlett Whitening Serum Brightly Ever After Serum / Acne Serum

['Paper Bag Victoria Secret']
['PAPER BAG VICTORIA SECRET']

['Double Tape 3M VHB 12 mm x 4,5 m ORIGINAL / DOUBLE FOAM TAPE']
['Double Tape VHB 3M ORIGINAL 12mm x 4.5mm Busa Perekat']

['Maling TTS Canned Pork Luncheon Meat 397 gr']
['Maling Ham Pork Luncheon Meat TTS 397gr']

['Daster Batik Lengan pendek - Motif Acak / Campur - Leher Kancing
['DASTER PIYAMA KATUN JEPANG(TIDAK BISA PILIH MOTIF & WARNA)']

['Nescafe \\xc3\\x89clair Latte 220ml']
['Nescafe Eclair Latte Pet 220 Ml']
```

Image Perceptual Hash

- 28,735 unique image phash in train data
- Size ranges from 1 to 26
- **89% size 1**, 8% size 2, 2% size 3
- Image phash is mostly unique
- **May not be useful** for predicting matching products

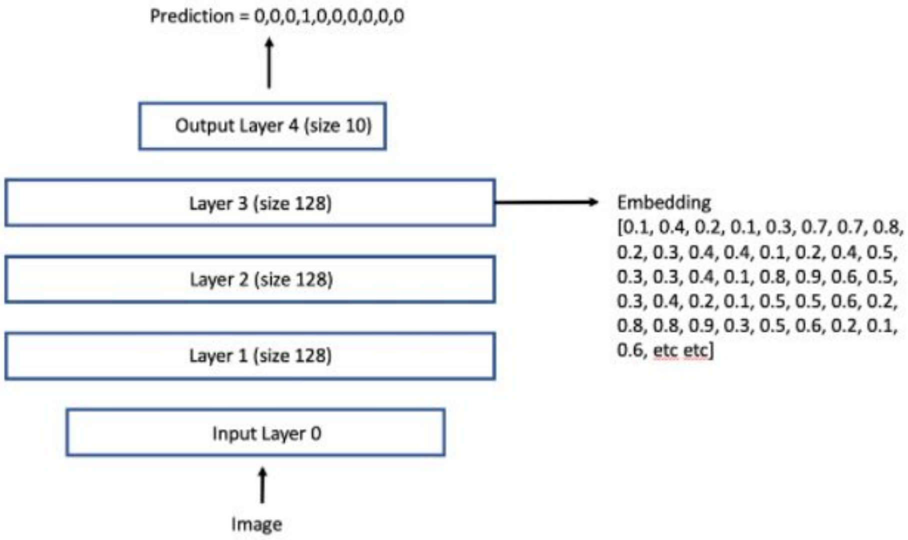


3. Image Embedding

Feature Embedding with EfficientNet

- EfficientNetB4: convolutional neural network pre-trained on ImageNet
- Generate embeddings from 2nd last layer for each image:

34,250 images x 1,792 features

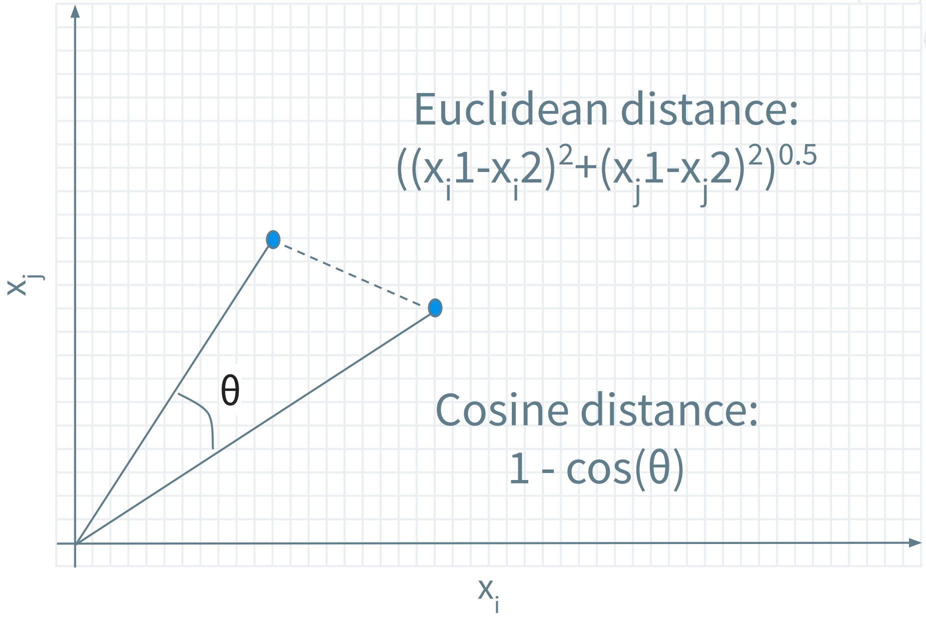


Source: https://www.kaggle.com/c/shopee-product-matching/discussion/226279

sklearn / cuML Nearest Neighbours

- sklearn.NearestNeighbors (CPU)
- cuML.NearestNeighbors (GPU)
- From (34250, 1792) feature matrix, calculate **nearest 51 neighbours** of each point using either Euclidean or cosine distance
- Returns **distances** and **indices** of nearest neighbours of each point: (34250, 51) matrices

Distance calculation of 2 points in 2 dimensions



Making Predictions

- From **distances** and **indices** of nearest 50 neighbours, set **distance threshold** to obtain predictions
- For example below, all indices below 0.2 distance will be assigned as predictions

Product	Distances	Indices	Threshold	Prediction
A	[**0, 0, 0.1**, 0.4, 0.5]	[**A, B, C**, D, E]		A, B, C
B	[**0, 0, 0.15**, 0.3, 0.6]	[**B, A, C**, D, E]		B, A, C
C	[**0, 0.1, 0.15**, 0.5, 0.6]	[**C, A, B**, D, E]	0.2	C, A, B
D	[**0, 0.1**, 0.3,0.4, 0.5]	[**D, E**, B, A, C]		D, E
E	[**0, 0.1**, 0.5, 0.6,0.6]	[**E, D**, A, B, C]		E, D

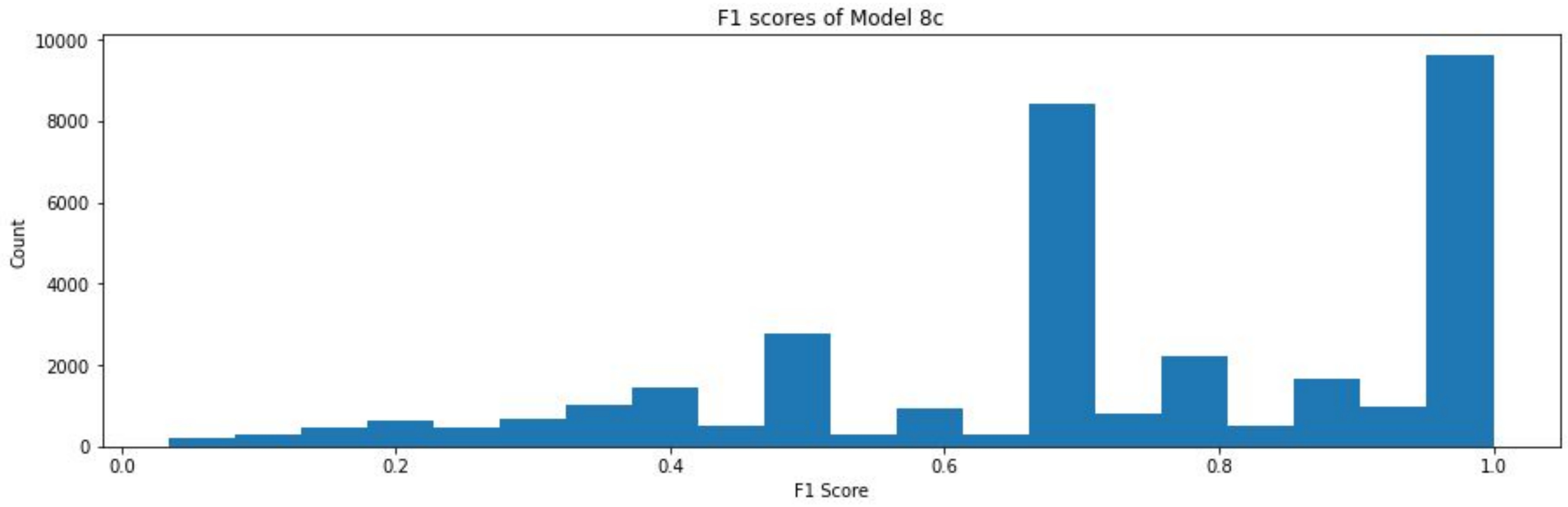
Results

- Default and re-trained EfficientNetB4 were used to generate image embeddings
- From feature matrix, obtain nearest neighbours and **grid search** various **distance thresholds** to find best score

No	Model	Euclidean Threshold	F1 Score	Cosine Threshold	F1 Score
0	Default EfficientNetB4	5	0.634	0.167	0.652
1	B4 with top_conv retrained (batch:32, epochs:3)	11	0.656	0.167	0.673
2	B4 with block7b_project_conv, top_conv retrained (batch:32, epochs:3)	13	0.654	0.2	0.685
3	B4 with block7b, top_conv retrained (batch:32, epochs:3)	11	0.665	0.2	0.681
4	Entire B4 retrained (batch:8, epochs:10)	8	0.637	0.167	0.634
5	Entire B4 retrained (batch:8, epochs:5)	8	0.632	0.133	0.629
6	B4 with block7a, block7b, top_conv retrained (batch:32, epochs:3)	18	0.684	0.2	0.701
7	B4 with block7b, top_conv retrained (batch:32, epochs:6)	11	0.662	0.233	0.679
8	B4 with block7a, block7b, top_conv retrained (batch:32, epochs:6)	20	0.675	**0.233**	**0.710**

Results

Distribution of scores for best image model:



Results

Sample predictions of best image model:

Product

Actual matches

Score:
$(2 \times 2) / (2 + 6) = 0.5$

4. Text Embedding

TF-IDF Vectorizer

- Remove English + Indonesian stop words from titles
- Lower case all words
- Regex tokenizer: [a-zA-Z0-9]+
- Fit transform using sklearn TfidfVectorizer
- **34,250 x 25,023 sparse feature matrix**

Google LaBSE

- Language-agnostic BERT Sentence Embedding
- Semantic embedding of multilingual sentence inputs
- BERT tokenizer:

```
['paper', 'bag', 'victoria', 'secret']
['double', 'tape', '3m', 'v', '##hb', '12', '4', '5', 'double', 'foam', 'tape']
['maling', 'tts', 'canne', '##d', 'pork', 'lunch', '##eon', 'meat', '397']
```

- **34,250 x 768 feature matrix**

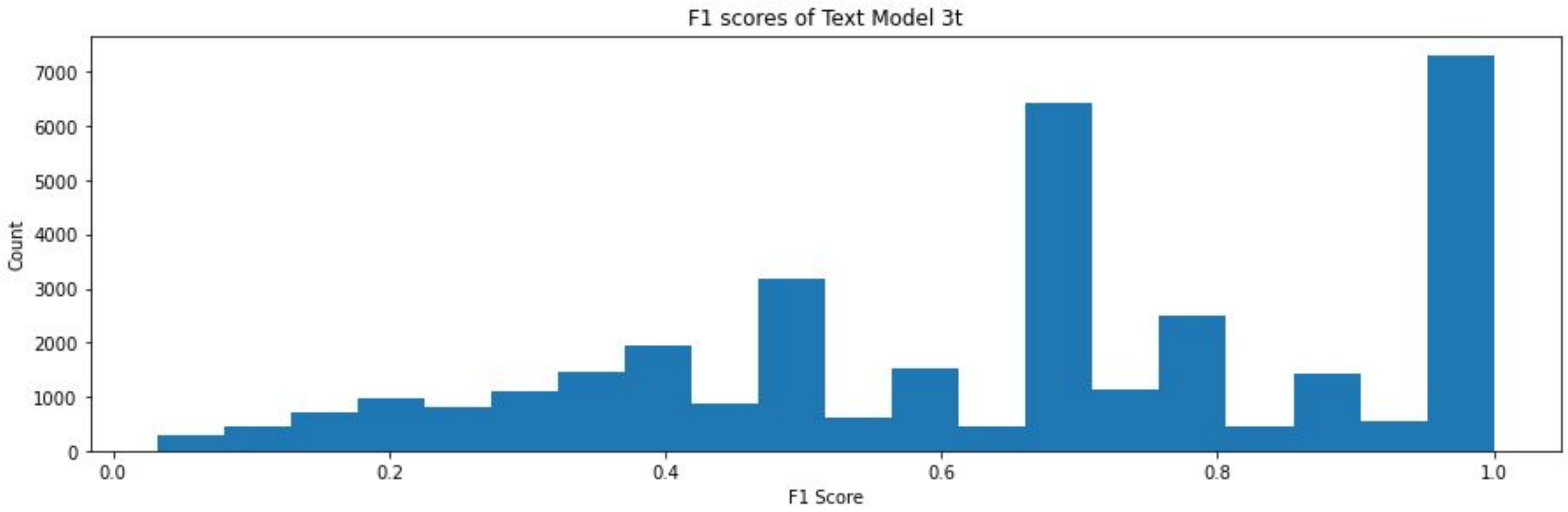
Modelling / Results

- Apply NearestNeighbors algorithm on feature matrix
- Grid search various distance thresholds

No	Tokens	Embedding Model	Distance Threshold	F1 Score
1	All stop words, [a-zA-Z0-9]+ regex tokenizer	TF-IDF vectorizer	Cosine 0.433	0.6467
2	All stop words, [a-zA-Z0-9]+ regex tokenizer	LaBSE	Cosine 0.2	0.6229
3	No stop words, [a-zA-Z0-9]+ regex tokenizer	TF-IDF vectorizer	**Cosine 0.433**	**0.6489**
4	No stop words, [a-zA-Z0-9]+ regex tokenizer	LaBSE	Cosine 0.2	0.6210

Results

Distribution of scores for best text model:



Results

Sample predictions of best text model:

```
Showing predictions of model 3t of posting_id train_3386243561
Titles:
Double Tape 3M VHB 12 mm x 4,5 m ORIGINAL / DOUBLE FOAM TAPE
Double Tape VHB 3M ORIGINAL 12mm x 4.5mm Busa Perekat
DOUBLE TAPE BUSA 3M Pe Foam Tape 24mm x 4M ORIGINAL
DOUBLE TAPE BUSA 3M Pe Foam Tape 24mm x 4M ORIGINAL
DOUBLE TAPE BUSA 3M Pe Foam Tape 24mm x 4M ORIGINAL
Double Tip / Double Sided Tape Perekat 2 Sisi Joyko 6 mm x 15 yard Double Tape

Tokens:
double tape 3m vhb 12 mm x 4 5 m original double foam tape
double tape vhb 3m original 12mm x 4 5mm busa perekat
double tape busa 3m pe foam tape 24mm x 4m original
double tape busa 3m pe foam tape 24mm x 4m original
double tape busa 3m pe foam tape 24mm x 4m original
double tip double sided tape perekat 2 sisi joyko 6 mm x 15 yard double tape
```

Product

Actual matches

Score:
(2 x 2) / (2 + 6) = 0.5

Results

Sample predictions of best text model (images):

Product

Actual matches

Score:
$(2 \times 2) / (2 + 6) = 0.5$

5. Combined Predictions

Set Union of Image and Text Predictions

Image prediction:

Score: 0.667

Text prediction:

Paper Bag Victoria Secret

PAPER BAG VICTORIA SECRET

Score: 1.0

Set union:

Score: 1.0

Combined Embeddings

- Concatenate feature matrices
- Apply Standard Scaler
- Search nearest neighbours from **combined matrix**

Image Embedding Matrix	TF-IDF Embedding Matrix	LaBSE Embedding Matrix	Combined Embedding Matrix
34,250 x 1,792	34,250 x 25,023	-	34,250 x 26,815
34,250 x 1,792	-	34,250 x 768	**34,250 x 2,560**
34,250 x 1,792	34,250 x 25,023	34,250 x 768	34,250 x 27,583

Soft Distance Threshold

Instead of fixed distance threshold for all predictions, use a **ratio of average distance** of nearest neighbours (e.g. 0.5)

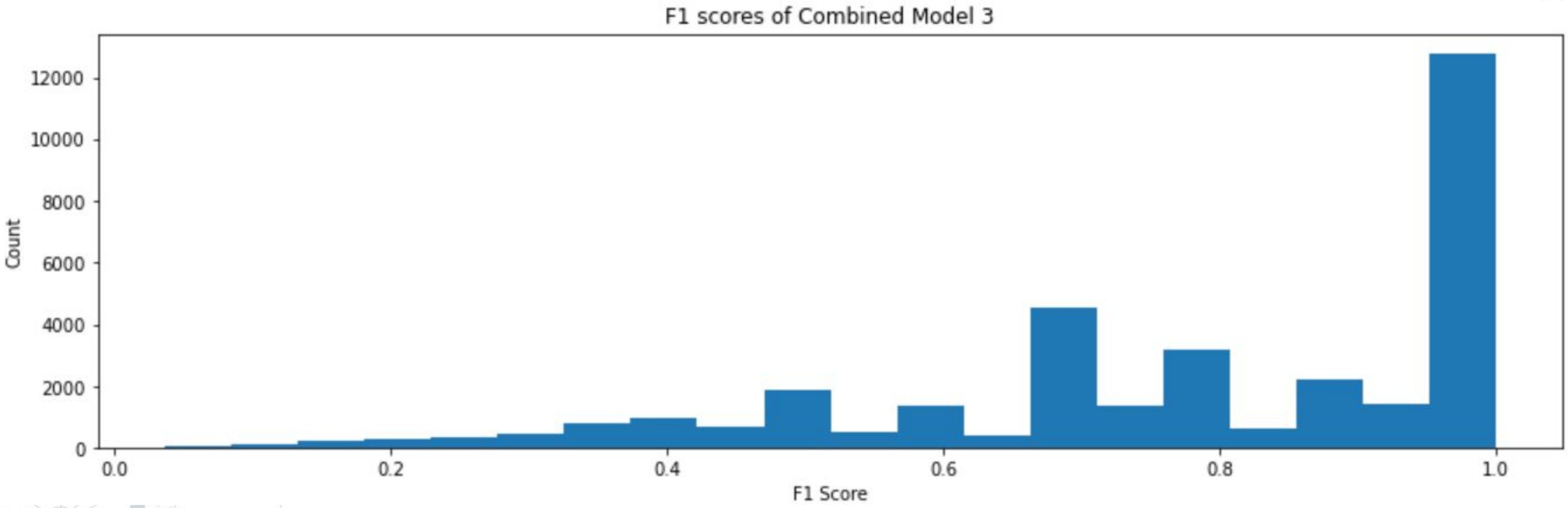
Product	Distances	Indices	Fixed Threshold	Average Distance	**Soft Threshold** (0.5 x average distance)	New Predictions	Score
A	[**0, 0**, 0.1, 0.4, 0.5]	[**A, B**, C, D, E]	0.2	0.2	0.1	A, B	1.0
B	[**0, 0**, 0.15, 0.3, 0.6]	[**B, A**, C, D, E]		0.21	0.105	B, A	1.0
C	[**0, 0.1**, 0.15, 0.5, 0.6]	[**C, A**, B, D, E]		0.27	0.135	C, A	0.4
D	[**0, 0.1**, 0.3,0.4, 0.5]	[**D, E**, B, A, C]		0.26	0.13	D, E	1.0
E	[**0, 0.1**, 0.5, 0.6,0.6]	[**E, D**, A, B, C]		0.36	0.18	E, D	1.0
						Average Score	**0.88**

Final Scores

No	Combination	Soft Distance Threshold (Ratio of average distances)	Train F1 Score	Kaggle Test F1 Score
1	Set union of best image + best TF-IDF models	Image: 0.62 TF-IDF: 0.56	0.773	0.724
2	Combined embeddings of best image + best LaBSE models	0.72	0.766	0.707
3	Set union of best image + best TF-IDF + model 2	Image: 0.5 TF-IDF: 0.45 Model 2: 0.7	**0.783**	**0.728**
4	Set union of best image + best TF-IDF + best LaBSE models	Image: 0.6 TF-IDF: 0.5 LaBSE: 0.4	0.775	0.726

Final Scores

Distribution of scores for best combined model:



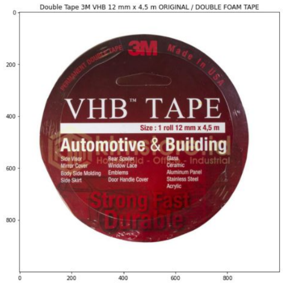
Sample Predictions

Matches:

Predictions:

Sample Predictions

Matches:



Predictions:

6. Conclusions and Recommendations

Model Analysis

- Identical or highly similar images/titles can be identified by the models
- Challenge lies in **combining image and text predictions** and setting the **distance heuristic** to make the right number of predictions
- Setting a **soft distance threshold** reduces excessive predictions and improves precision
- Using **ensembles** of different image and text embeddings improves recall

Challenges

Models perform poorly where product matches have **dissimilar images and titles**

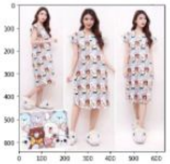
Matches:

```
Showing matches of posting_id train_2406599165
Titles:
Daster Batik Lengan pendek - Motif Acak / Campur - Leher Kancing (DPT001-00) Batik karakter Alhadi
DASTER PIYAMA KATUN JEPANG(TIDAK BISA PILIH MOTIF & WARNA)
```

Text predictions:

```
Showing predictions of model 3t of posting_id train_2406599165
Titles:
Daster Batik Lengan pendek - Motif Acak / Campur - Leher Kancing (DPT001-00) Batik karakter Alhadi
Daster Batik Lengan pendek - Motif Acak / Campur - Leher Kancing (DPT001-00) Batik karakter Alhadi
Daster Batik Lengan pendek - Motif Acak / Campur - Leher Kancing (DPT001-00) Batik karakter busui
Daster Batik Lengan pendek - Motif Acak / Campur - Leher Kancing (DPT001-00) Batik karakter IKHLAS
Daster Batik Bali Lengan pendek - Motif Acak / Campur - Leher Kancing BUSUI - BUMIL - Batik Alhadi
Daster payung klok motif acak/campur leher kancing busui bumil (DPT001-00) Batik FA
Daster Payung Bali JUMBO XXL, Motif Acak / Campur, Leher Kancing Bumil Busui (DPT005), Batik Alhadi
```

Image predictions:



Recommendations

- More data/metadata in addition to images and titles would be useful to generate a **more complete feature space**
  - Do same products come from the same shop, same supplier, same location etc?
- Product matching could also involve **other approaches** in addition to machine learning, e.g. user behavior
  - If users that view product A always view product B, it could be that A and B are the same

Thank You

Any questions?

Slides credit: Slides Carnival