A Street Group Address Matching Algorithm

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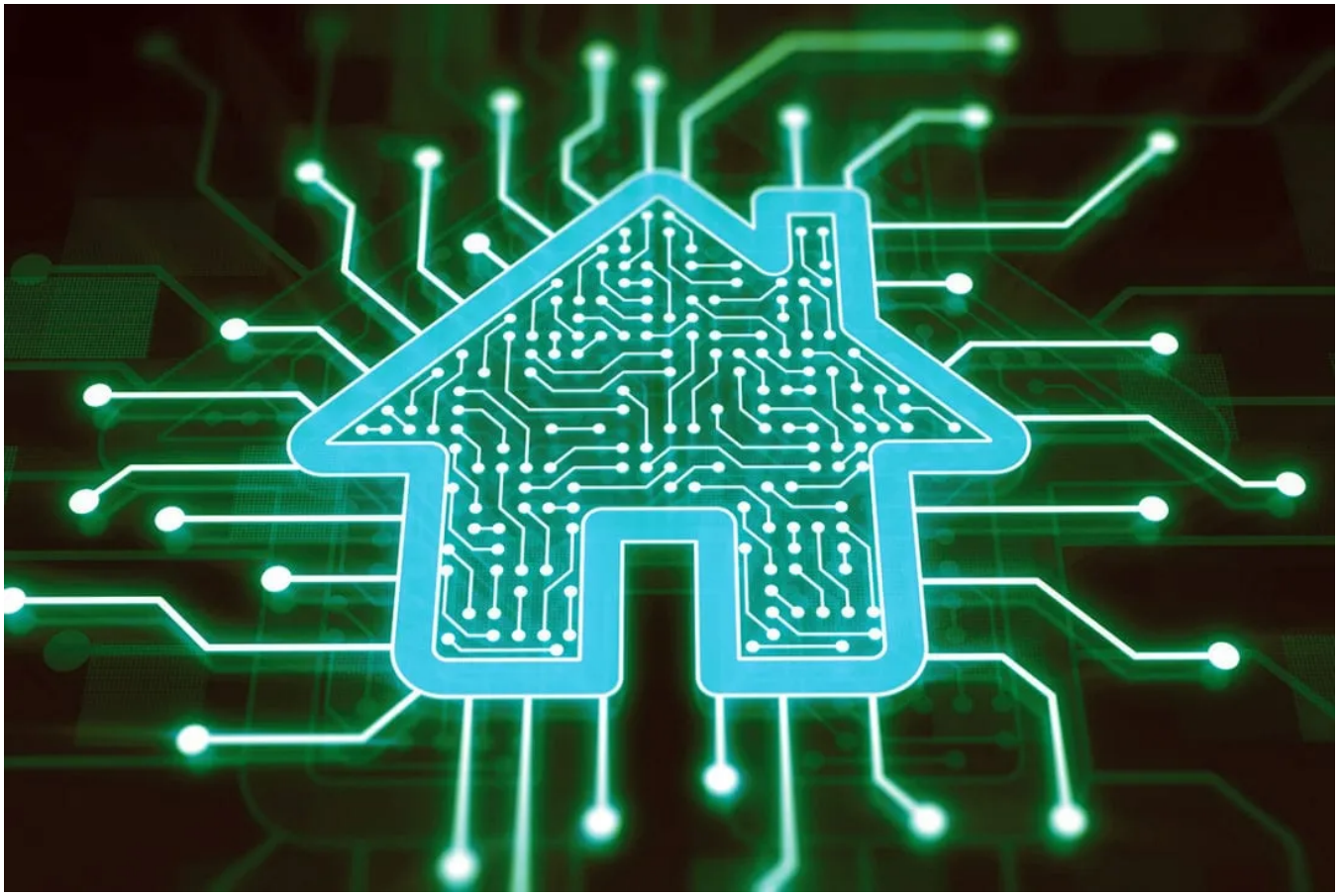

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Address matching — the process of identifying pairs of address records referring to the same spatial footprint — is increasingly required for enriching data quality in a wide range of real-world applications.

Street Group is one of the fastest-growing PropTech companies in the UK, and is dedicated to improving the experience of agents and their clients whilst they navigate the process of moving home. Our broad range of innovative software products relies on the quality and consistency of our UK property database. The process of matching the original raw-string addresses from our various database ingestion sources to their respective standard Royal Mail postal address Unique Property Reference Number (UDPRN) plays a fundamental role in ensuring the reliability of our data. However, the linkage of these raw-address records can present a challenge to unlocking the full potential of our integrated (spacial) data sources.

For this purpose, we designed a state-of-the-art address matching model to link the input raw-addresses to their corresponding Royal Mail UDPRNs.

The Machine Learning / NLP solution

With an input raw-address and its postcode, we can look up the Royal Mail database to obtain the corresponding UDPRNs and addresses for that postcode. The goal is to develop an NLP solution that will score the similarity between address elements (see table below). Using a simple rule-based model, it is possible to obtain certain address matches. However, as source raw-addresses become more disorganised and unformatted, this approach won't always work — e.g. " *10A 3 FLOOR FULHAM BROADWAY "* could confuse a rule-based model to select *"flat 10 3 fulham broadway"* as opposed to *"third floor flat 10a fulham broadway"*. This indicates that there is significant room for improvement using some more advance NLP /ML techniques.

Input raw-address	Input postcode	UDPRN (encoded)	RM address	Postcode
10A 3 FLOOR FULHAM BROADWAY	SW6 1AA	eyJ1ZHBybiI6ICIyNzY3NzYxMSJ9	11 fulham broadway	SW6 1AA
		eyJ1bXBybiI6ICI1NTEyODQ0NyJ9	flat 2 7 fulham broadway	SW6 1AA
		eyJ1ZHBybiI6ICIyMzgzNTYyNiJ9	sia hair & beauty 8 fulham broadway	SW6 1AA
		eyJ1bXBybiI6ICI1NTEyODQ0OCJ9	flat 3 7 fulham broadway	SW6 1AA
		eyJ1ZHBybiI6ICIyMzgzNTYzNiJ9	william hill bookmakers 12-14 fulham b	SW6 1AA
		eyJ1bXBybiI6ICI1NTEyODQ1MyJ9	flat 8 7 fulham broadway	SW6 1AA
		eyJ1bXBybiI6ICI1NjAzNTQyNCJ9	second floor flat 10a fulham broadway	SW6 1AA
		eyJ1bXBybiI6ICI1NTEyODQ1MCJ9	flat 5 7 fulham broadway	SW6 1AA
		eyJ1bXBybiI6ICI1NjAzNTQyNiJ9	third floor flat 10a fulham broadway	SW6 1AA
		eyJ1bXBybiI6ICI1MjU1NjY0MCJ9	flat b 12-14 fulham broadway	SW6 1AA
		eyJ1bXBybiI6ICI1NTEyODQ1MSJ9	flat 6 7 fulham broadway	SW6 1AA
		eyJ1ZHBybiI6ICIyMzgzNTYyNCJ9	whole foods 3 fulham broadway	SW6 1AA
		eyJ1bXBybiI6ICI1NTEyODQ1NCJ9	flat 9 7 fulham broadway	SW6 1AA
		eyJ1bXBybiI6ICI1MjU1NjYzOSJ9	flat a 12-14 fulham broadway	SW6 1AA
		eyJ1ZHBybiI6ICI1NDAwOTA0MyJ9	flat 10 3 fulham broadway	SW6 1AA

Our current model uses multiple different rules to assess whether a pair of addresses is a match. This model leaves a big proportion of our dataset un-matched due to the above mentioned complications when the input raw-address has a different format. However, the input addresses that the current model manages to find a UDPRN for can be used as a dataset for training a machine learning model.

Provided we know the matching UDPRN for several million properties in the UK, we can generate a highly skewed training dataset for binary classification, such as:

Input raw-address	RM address	Label
10A 3 FLOOR FULHAM BROADWAY	11 fulham broadway	0
10A 3 FLOOR FULHAM BROADWAY	flat 2 7 fulham broadway	0
10A 3 FLOOR FULHAM BROADWAY	sia hair & beauty 8 fulham broadway	0
10A 3 FLOOR FULHAM BROADWAY	flat 3 7 fulham broadway	0
10A 3 FLOOR FULHAM BROADWAY	william hill bookmakers 12-14 fulham b	0
10A 3 FLOOR FULHAM BROADWAY	flat 8 7 fulham broadway	0
10A 3 FLOOR FULHAM BROADWAY	second floor flat 10a fulham broadway	0
10A 3 FLOOR FULHAM BROADWAY	flat 5 7 fulham broadway	0
10A 3 FLOOR FULHAM BROADWAY	third floor flat 10a fulham broadway	1
10A 3 FLOOR FULHAM BROADWAY	flat b 12-14 fulham broadway	0
10A 3 FLOOR FULHAM BROADWAY	flat 6 7 fulham broadway	0
10A 3 FLOOR FULHAM BROADWAY	whole foods 3 fulham broadway	0
10A 3 FLOOR FULHAM BROADWAY	flat 9 7 fulham broadway	0
10A 3 FLOOR FULHAM BROADWAY	flat a 12-14 fulham broadway	0
10A 3 FLOOR FULHAM BROADWAY	flat 10 3 fulham broadway	0

In order to generate the features to be fed into our ML model, we followed some of the preprocessing steps from *Y. Lin et al. (2020)*:

1. We parsed all address strings with the well established pre-trained Conditional Random Field (CRF) address parser library *libpostal*.

```
>> parse_address('10a 3 floor FULHAM BROADWAY', language='EN',
country='GB')

[('10a', 'house_number'), ('3 floor', 'level'), ('fulham broadway',
'road')]
```

There are additional address-elements supported by *libpostal* and these can be provided as padding generating an address-element vector of the form:

```
vector1 = [nan, nan, nan, '10a', nan, nan, '3 floor', nan, nan, nan,
nan, 'fulham broadway', nan, nan, nan, nan, nan, nan, nan, nan]
```

Similarly for the corresponding Royal Mail address pair

```
>> parse_address('third floor flat 10a fulham broadway',
language='EN', country='GB')

[('10a', 'house_number'), ('third floor flat', 'level'), ('fulham
broadway', 'road')]
```

and corresponding address vector

```
vector2 = [nan, nan, nan, '10a', nan, nan, 'third floor flat', nan,
nan, nan, nan, 'fulham broadway', nan, nan, nan, nan, nan, nan, nan,
nan]
```

2. Compute the Jaro-Winkler similarity in between address-element vector-components generating a comparison vector.

```
comp_vector = [0. , 0. , 0. , 1. , 0. , 0. , 0.3, 0. , 0. , 0. , 0.
, 1. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ]
```

3. Train FastText embeddings on all Royal Mail addresses using the address-elements given by *libpostal* as tokens. Once trained, calculate the cosine similarity between the embedding representation of *vector1* and *vector2* and add the result to the *comp_vector*.

4. Calculate the Jaccard similarity between the input strings.

5. Add additional comparative features between input strings such as number of non-null address-elements in *vector1* and *vector2* respectively, and number of characters in each input address strings.

The resulting comparative vector for each address pair can be formatted into a pandas DataFrame as illustrated below. Often the cosine similarity (*cossim*) and Jaccard similarities (*jaccard_similarity*) will give a strong indication of what the correct address match is but this won't always be the case.

	house	category	near	house_number	road	unit	level	staircase	...	world_region	jaccard_similarities	count_notNan_1	count_notNan_2	sum_notNan_1	sum_notNan_2	cossim	labels
0	0.0	0.0	0.0	1.00	1.0	0.0	0.0	0.0	...	0.0	1.000000	2.0	2.0	18.0	18.0	1.000000	1
1	0.0	0.0	0.0	0.00	1.0	0.0	0.0	0.0	...	0.0	0.666667	2.0	2.0	18.0	19.0	0.999807	0
2	0.0	0.0	0.0	0.61	1.0	0.0	0.0	0.0	...	0.0	0.785714	2.0	2.0	18.0	19.0	0.999788	0
3	0.0	0.0	0.0	0.61	1.0	0.0	0.0	0.0	...	0.0	0.785714	2.0	2.0	18.0	19.0	0.999822	0
4	0.0	0.0	0.0	0.00	1.0	0.0	0.0	0.0	...	0.0	0.714286	2.0	2.0	18.0	19.0	0.999754	0
5	0.0	0.0	0.0	0.61	1.0	0.0	0.0	0.0	...	0.0	0.846154	2.0	2.0	18.0	19.0	0.999774	0
6	0.0	0.0	0.0	0.00	1.0	0.0	0.0	0.0	...	0.0	0.714286	2.0	2.0	18.0	19.0	0.999759	0
7	0.0	0.0	0.0	0.00	1.0	0.0	0.0	0.0	...	0.0	0.666667	2.0	2.0	18.0	19.0	0.999781	0
8	0.0	0.0	0.0	0.00	1.0	0.0	0.0	0.0	...	0.0	0.785714	2.0	2.0	18.0	19.0	0.999746	0
9	0.0	0.0	0.0	0.00	1.0	0.0	0.0	0.0	...	0.0	0.714286	2.0	2.0	18.0	19.0	0.999776	0

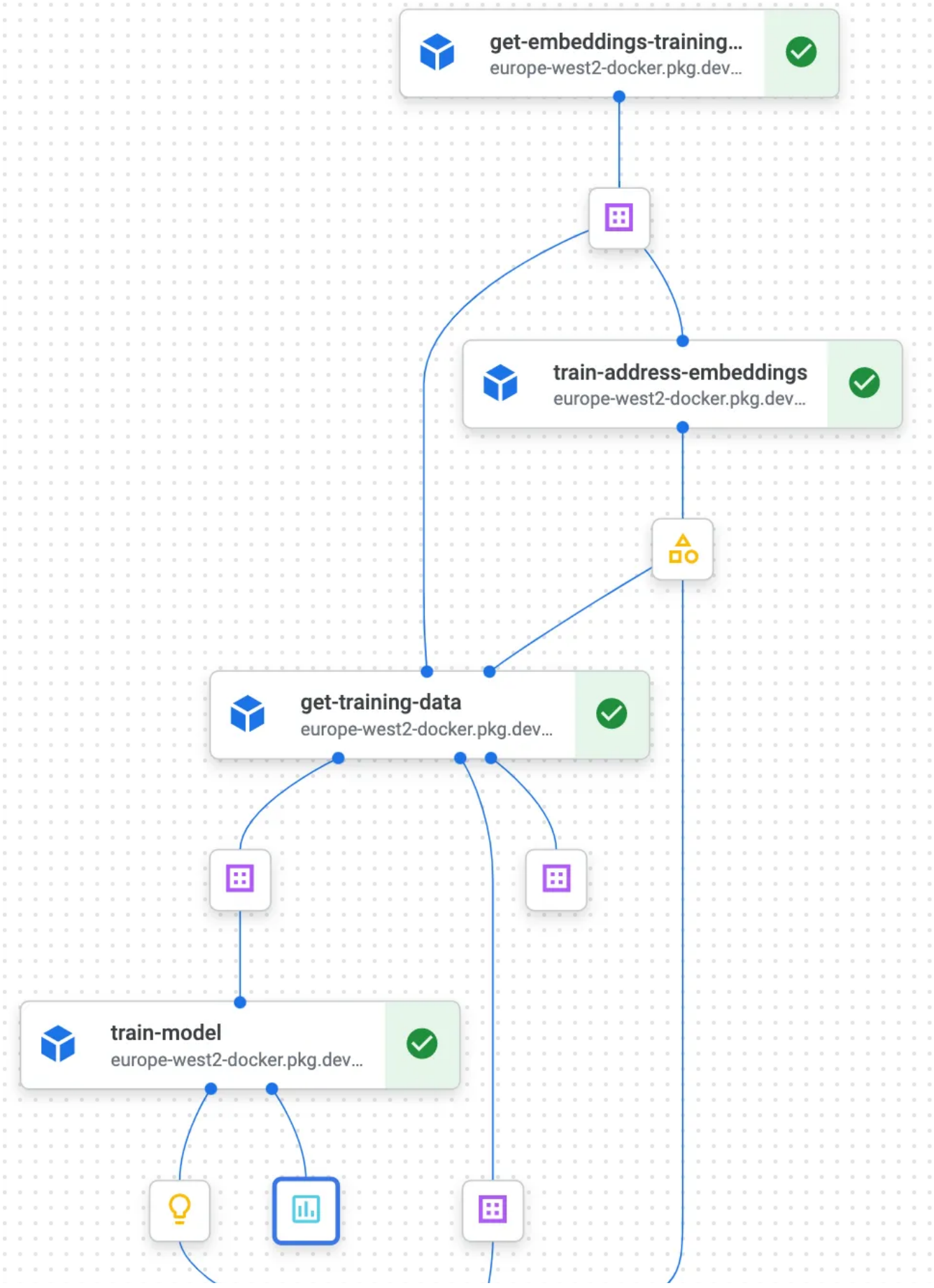
Finally, we trained an XGBoost binary classifier to predict whether a pair is a match based on the generated comparative features. Class weights needed to be passed to the constructor of the classifier, since there were about 95% of non-matching addresses (label 0) vs 5% of matches (label 1). As such, the contribution of the positive class to the loss function was scaled up to account for the class imbalance.

The model achieved a 99.1% precision on the known UDPRN dataset, the remaining

0.9% constituting errors made by the rule-based model that generated the labels. In addition, the model allowed us to address-match an additional 80% of the addresses without UDPRN, of which approximately 60% had a high confidence score (*i.e.* high XGBoost probability).

Deployment

The training of the embeddings, generation of the comparative features and training of the XGBoost classifier were deployed into a Kubeflow pipeline. The high scalability and exceptional metadata storage made Kubeflow one of our preferred deployment options. Kubeflow allowed us to customise the CPU and RAM needed at each step-component of the pipeline, which ultimately resulted in a cost optimisation.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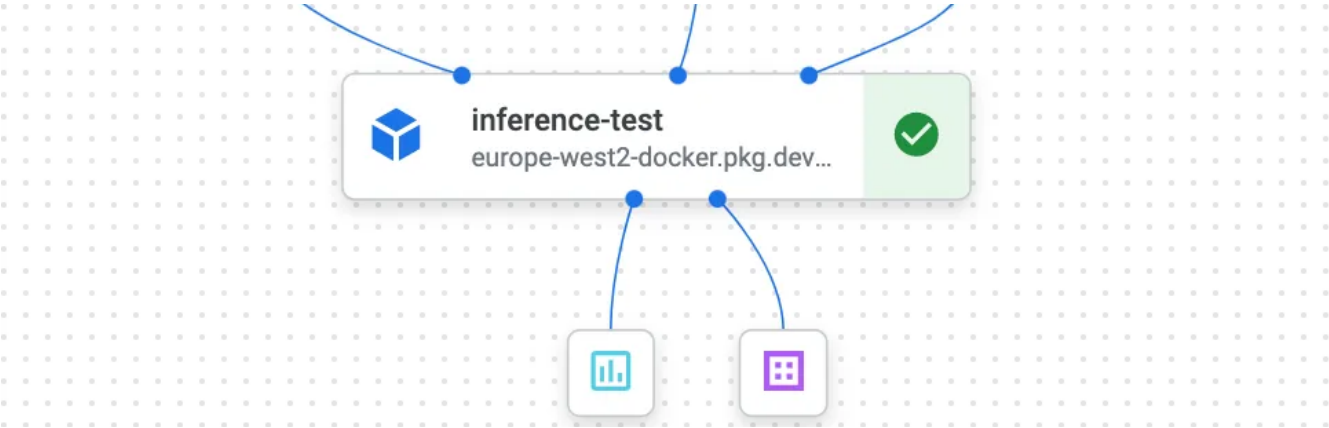

In addition to the Kubeflow pipeline, we also needed to have this model accessible via an API endpoint. The endpoint would fetch the necessary metadata objects from the pipeline (*i.e.* the trained model, the trained embeddings and the dictionary of addresses and postcodes) and, when given a raw-address and a postcode, returned an encoded UDPRN and the confidence score for the match — we chose FastAPI to serve the model. The deployment of this endpoint proved challenging due to the long loading times of the model within the created Docker image; the dictionary of addresses and the FastText embeddings are fairly large and take several minutes to load into memory, resulting in complications when using GCP cloud run. Finally, the endpoint was deployed using standalone Kubernetes with the model objects still being fetched from the Kubeflow pipeline.

Conclusion

This project was very instructive both from the perspective of developing the NLP model and its deployment. Other NLP solutions such as SiameseLSTM or simple cosine similarity models were also explored but the combination of CRFs and string similarity metrics with an XGBoost model proved to be the highest scoring in our data.

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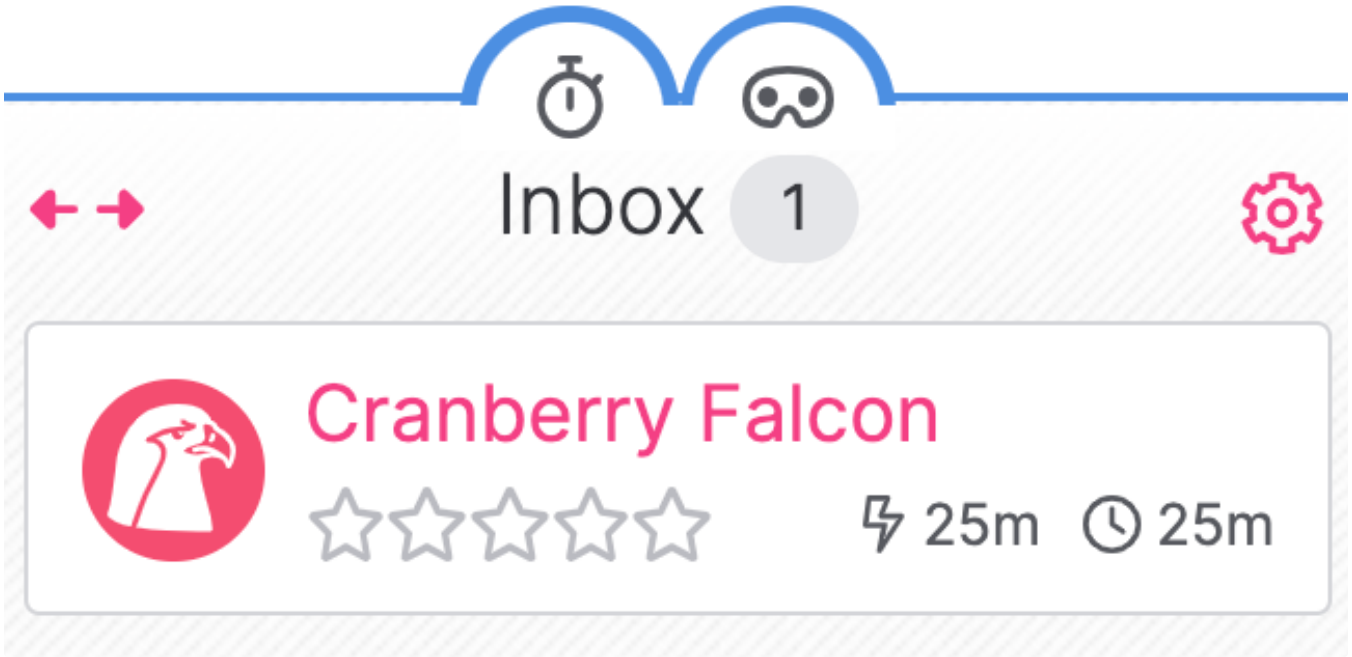

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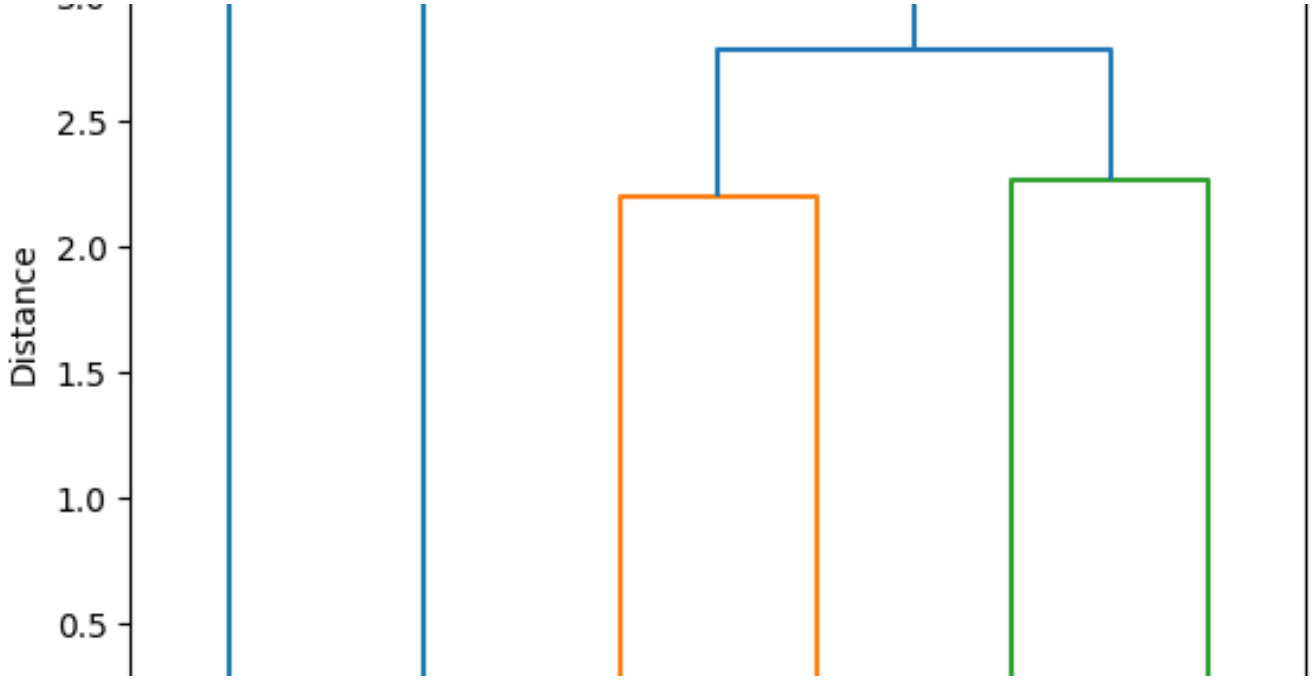

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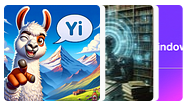

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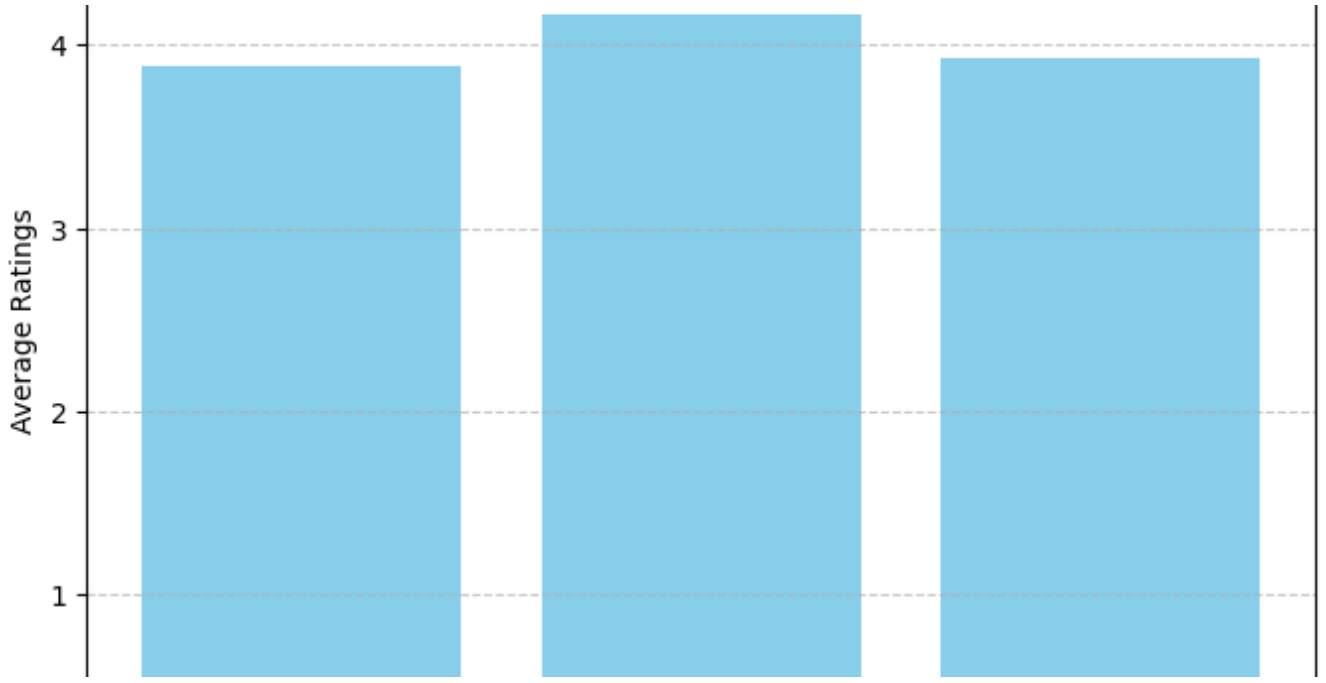

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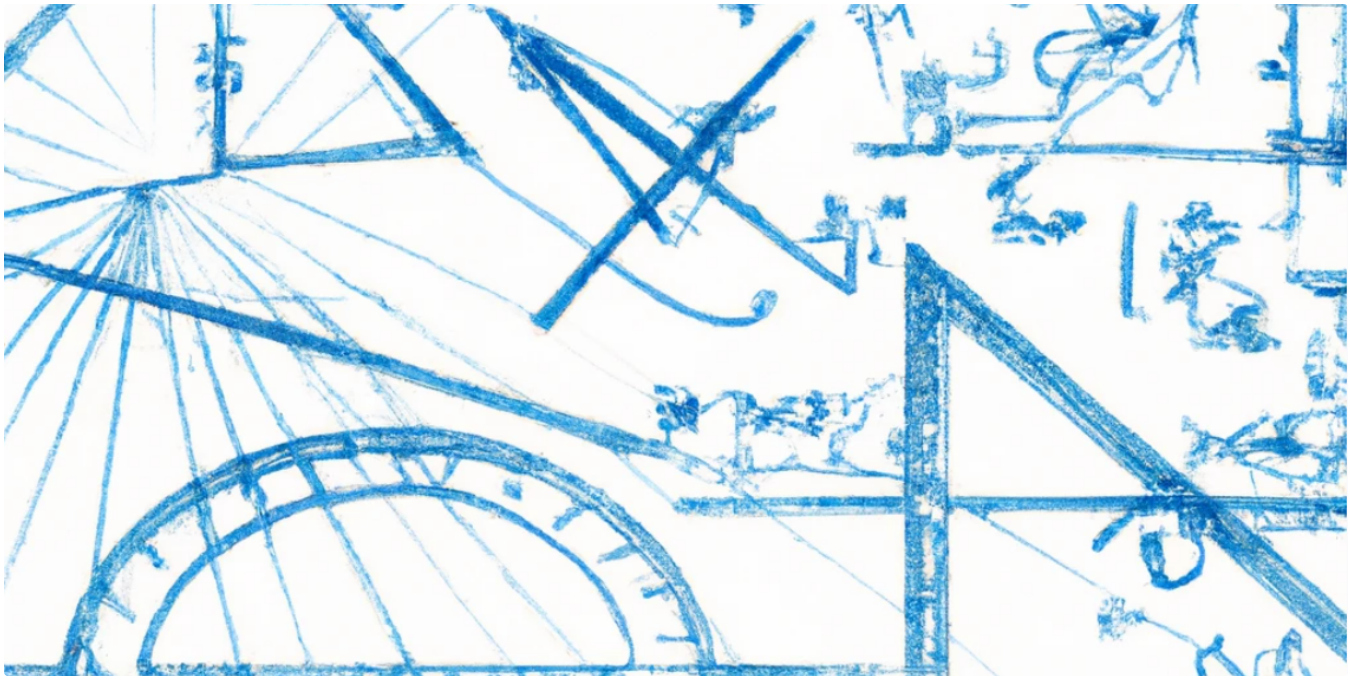

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