P2P buddy.ai

A Comprehensive Pantry-to-Plate System for
Ingredient Recognition and Recipe Recommendation

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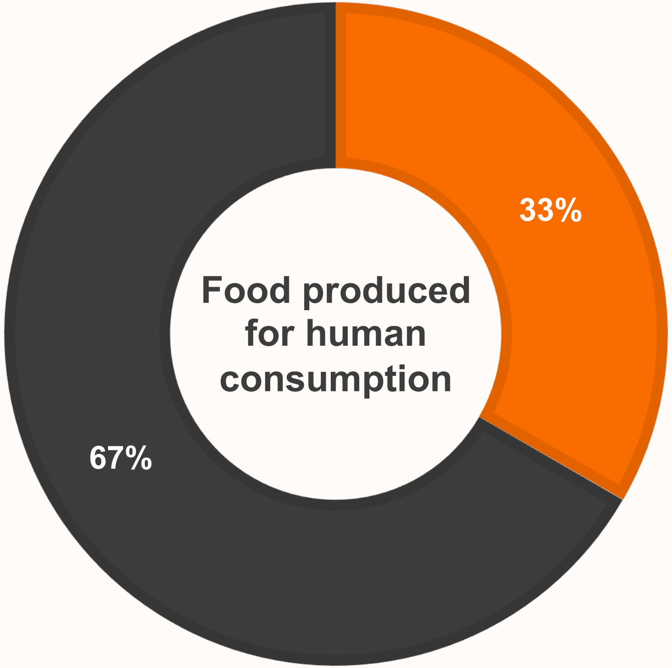
01

Current situation

Food waste is a complex global issue.



$1 trillion

wasted per year globally

Households are the largest contributor

>50%

ECONOMIC

SOCIAL

ENVIRONMENTAL

Singapore is no exception.

+23%

665mil kg of food thrown away in 2020 → **817mil kg** of food thrown away in 2021

50%: households

The rest: F&B premises, hawker centres, schools, hotels, malls, markets, and food manufacturers

24% of households often threw away spoilt or rotten food because they either bought too much food or did not realise that they had food hidden at the back of their fridge.

How might we help households deal with excess groceries in their kitchens?

02

Solution aim

Build an intelligent 2-in-1 tool

- Aim: to build a user-friendly and accurate ingredient recognition tool and recipe recommender
- Supervised computer vision machine learning
- For a start, we shall start with ingredients laid out on the kitchen countertop/pantry table

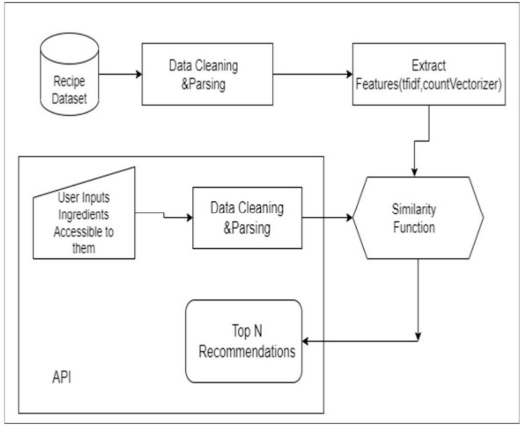


Fig. 3. Flowchart of recommendation system.

https://www.itm-conferences.org/articles/itmconf/pdf/2022/04/itmconf_icacc2022_02006.pdf

03

Data exploration

Overview:

Recipe dataset

https://themeatmen.sg/all-recipes/

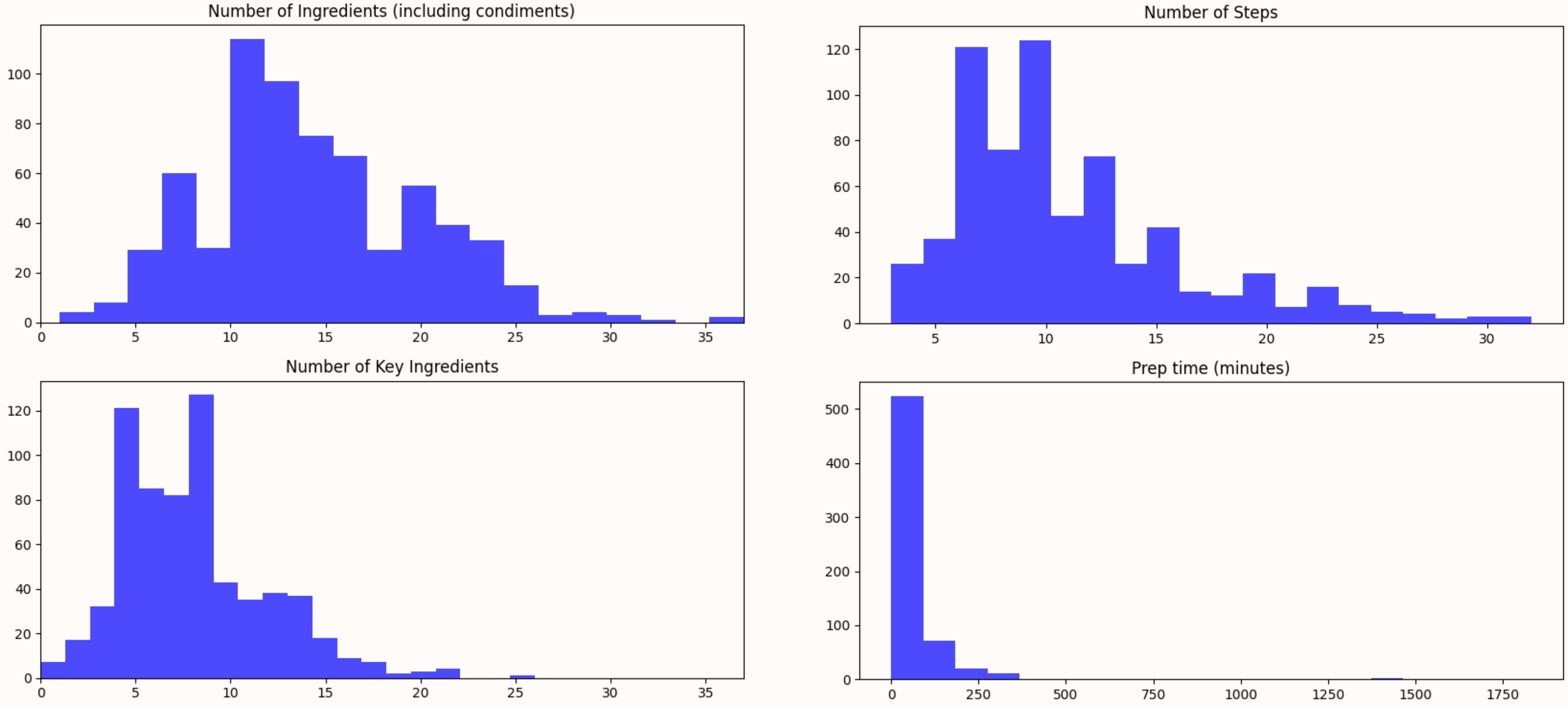
777
recipes

4
features

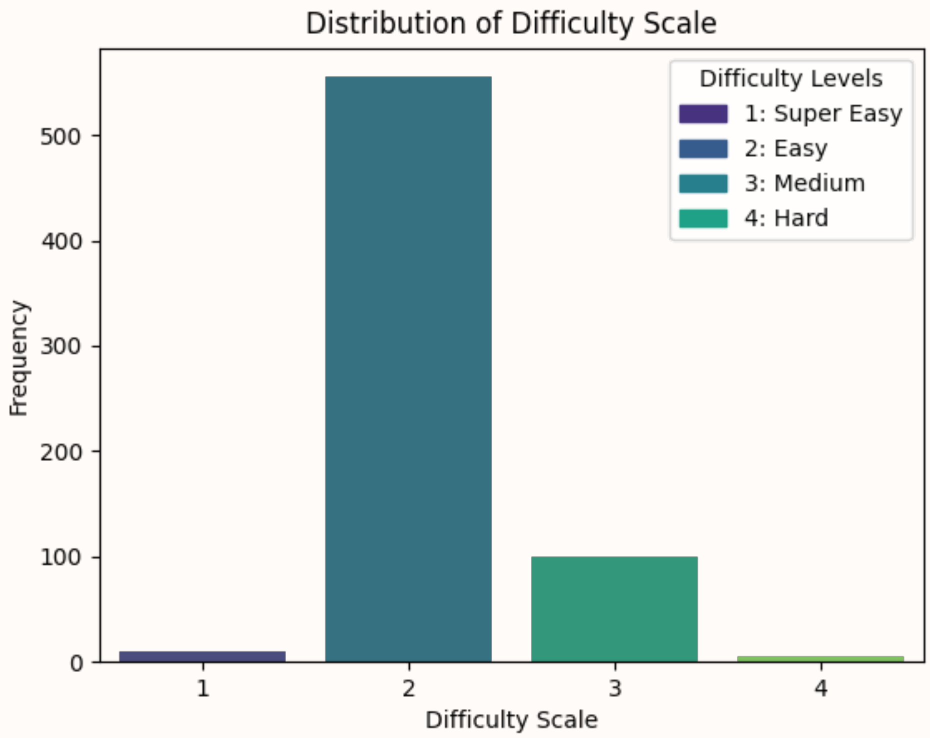
Text: Directions, ingredients
Numerical: prep time
Categorical: Difficulty

up to
51 recipes
missing ingredients / missing directions / missing prep time

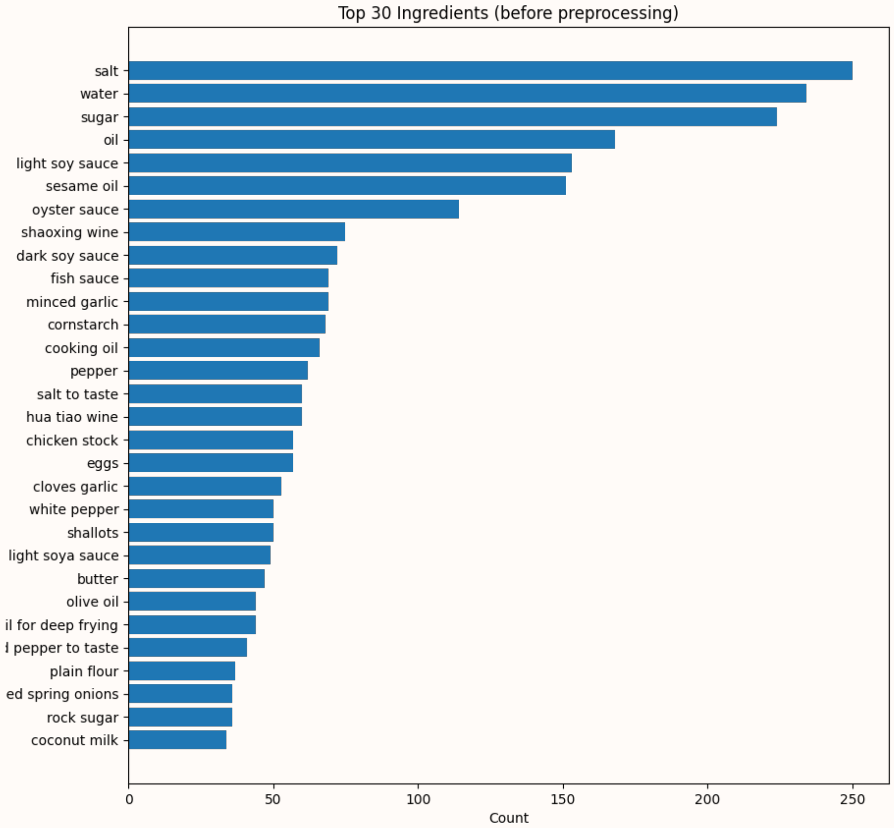
Variety of recipes

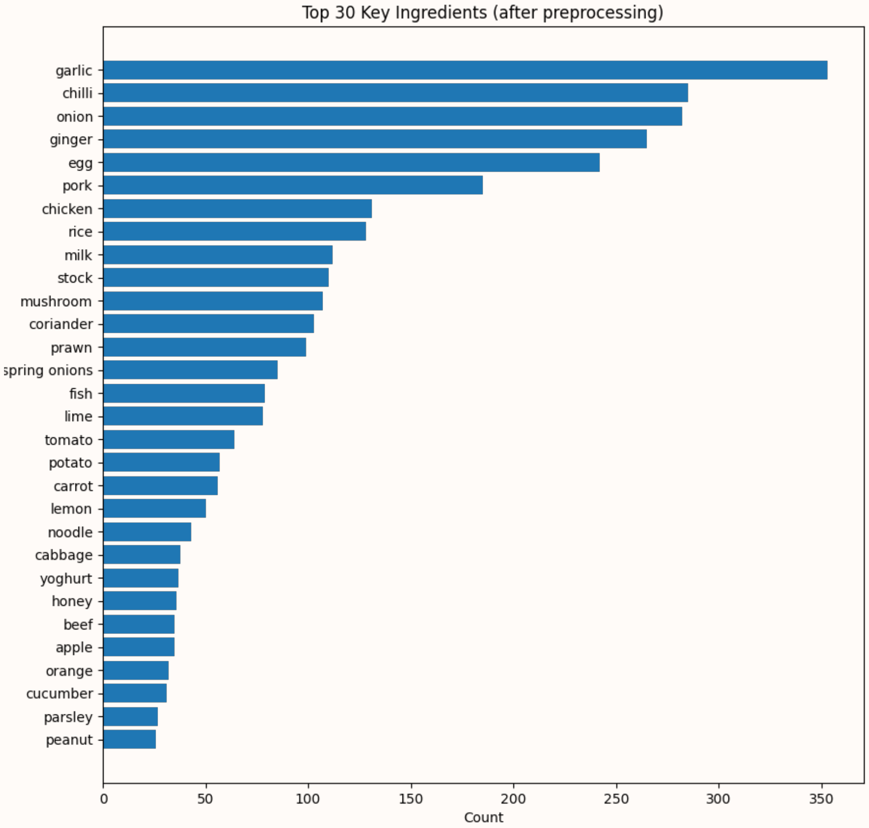


Variety of recipes



Top 30 ingredients





Overview:

Ingredient images dataset

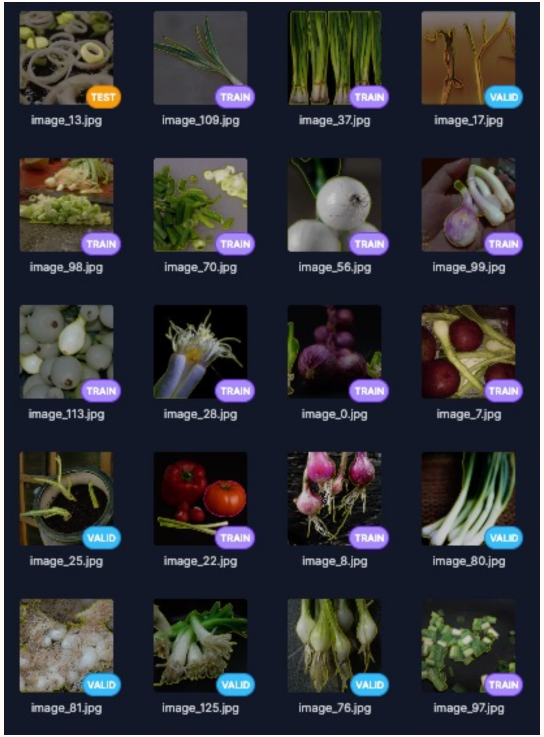
roboflow
FairPrice
flickr

Visually inspected for relevance

8,942
images

21,810
annotations

30
common
key ingredient classes



04

Modelling

Modelling:

workflow

preprocess

Resize

Train Augmentation &

Train-val-test split

Train 85% (6.5k → 13k)

Val 11% (1.6k)

Test 5% (716)

Custom training on Object Detection Models
(pretrained with COCO)

Roboflow

Yolov8s

Yolov8m

Model with Highest mAP proceeds

Tuning & Finalising model

Epochs

Optimiser

Learning rate

Momentum

Weight decay

Modelling:

evaluation summary

	Object detection model	mAP-50
Smaller image dataset (~4k images, 80 classes)	**Roboflow 3.0 (Fast)** 640px	62.9%
	Yolo v8 (small) 800px	50.3% (↓ 12.6pp)
Larger image dataset (~15.5k images, 30 classes)	**Roboflow 3.0 (Fast)** 640px	70.7% (↑ 7.8pp)
	Yolo v8 (small) 800px	**72.2%** (↑ 9.3pp)
	Yolo v8 (med) 640px	

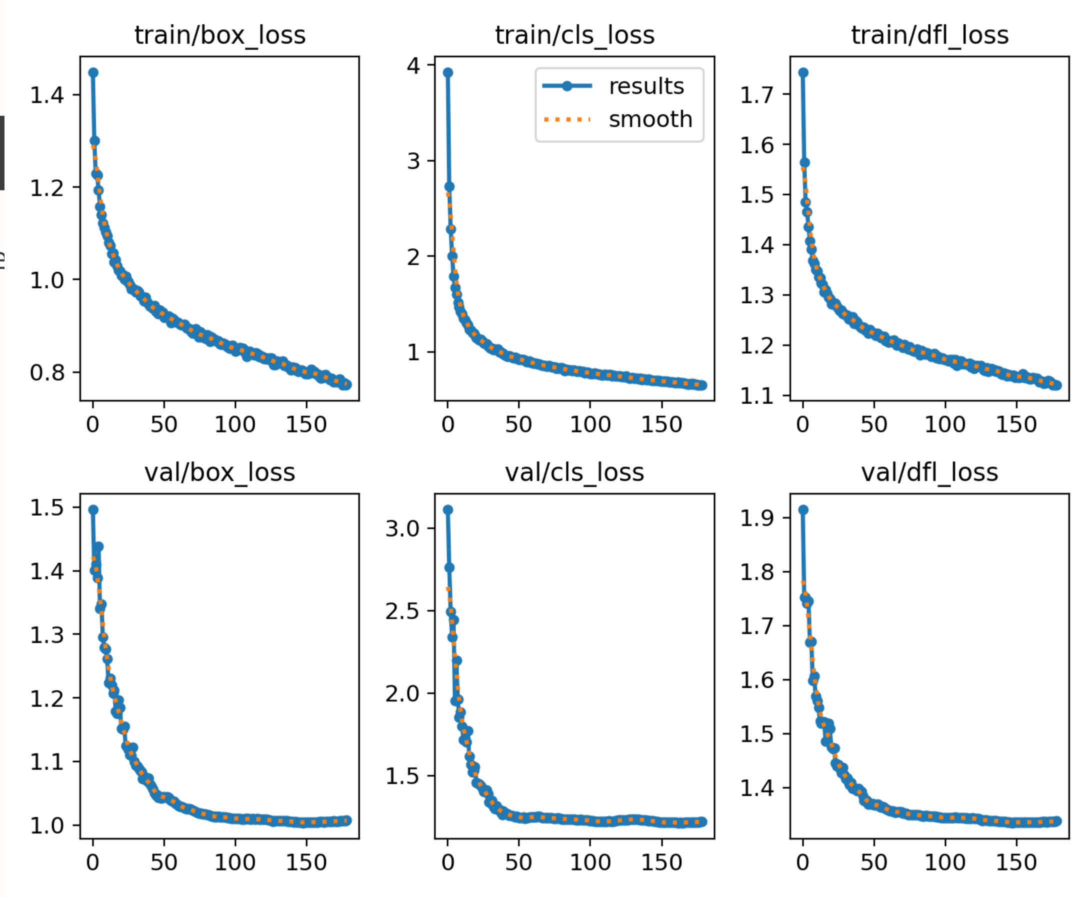
- includes train data augmentation
- Mean Average Precision (mAP) -50 refers to the mean average precision across all classes at Intersection-Over-Union (IOU) threshold of 0.5.

Modelling:

interpretat

Interpret mAP50 / precision-recall curve

Confusion matrix

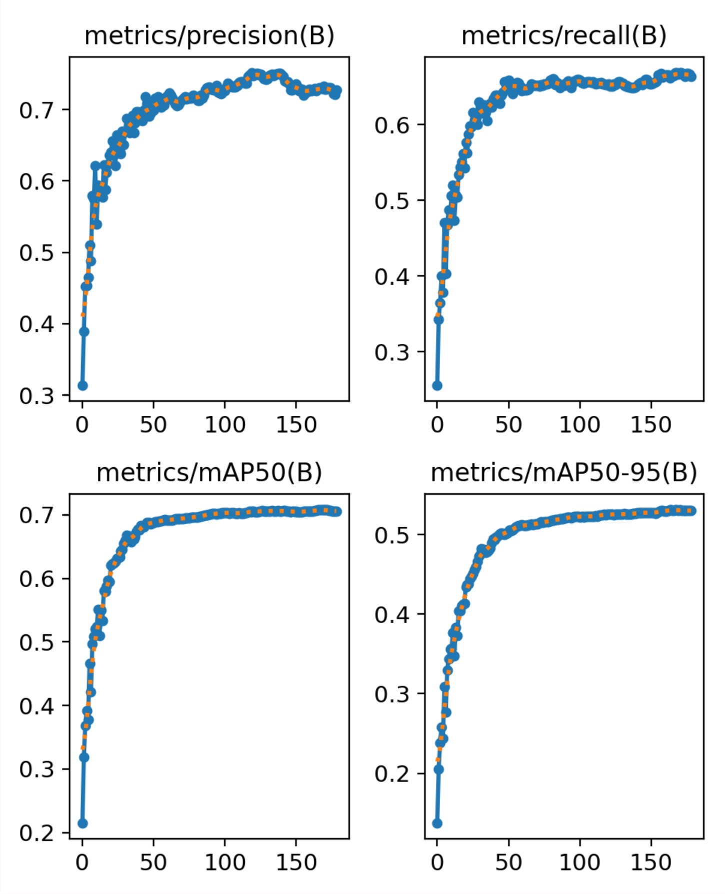


Modelling:

interpretation

Interpret mAP50 / precision-recall curve

Confusion matrix



05

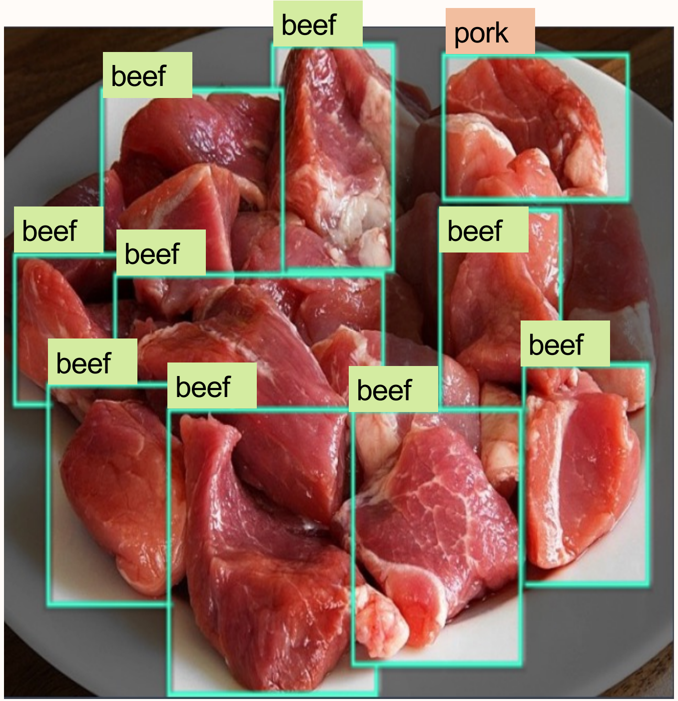
Insights and recommendations

Larger dataset increases precision

Precision varies across ingredient classes

Confused detection of similar ingredients

Ginger wrongly labelled as garlic, mushroom and onion.



Additional label: pork

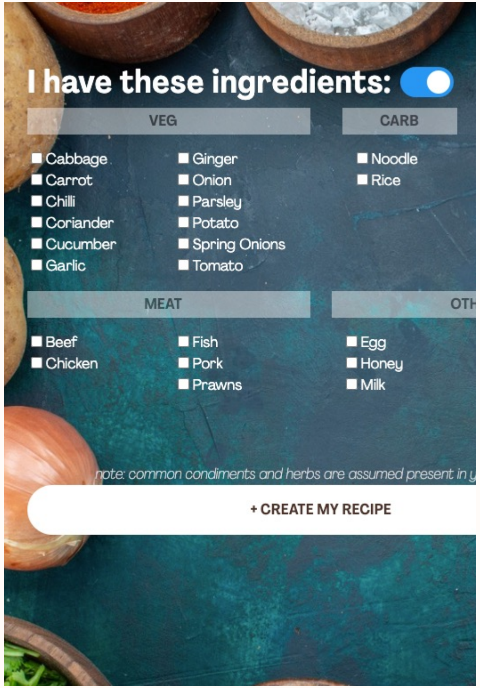
Recipe recommender

- TF-IDF
- Jaccard similarity score / Cosine similarity score

06

Demo of P2P buddy.ai

2-in-1:
Ingredient recognition & recipe recommender



Challenges and Key takeaways

- Data collection and cleaning (images) – have to be conscious of being brand agnostic, a lot of visual inspections to ensure relevant images, Image dataset building was tedious due to bounding boxes (hard to distinguish from reflections of packaging, occluded items.., types of packaging (e.g. frozen, vacuum, etc), cooked vs uncooked forms)

- Focus on fewer but key (common) classes, more images per class

- Data cleaning (recipe) – many interchangeable ingredient terms, some loosely related