AI-POWERED SOLUTIONS FOR THE RESTAURANT INDUSTRY

Leveraging LLMs for enhanced product categorization.

THE ERDÖS INSTITUTE DEEP LEARNING BOOTCAMP

Evaristo Villaseco Arribas & Davood Dar & Amir Kazemi-Moridani

Agenda



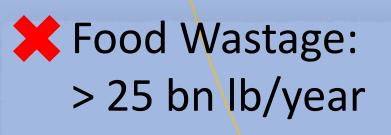
- I. Problem Statement
- II. Data Collection & Cleaning
- III. EDA
- IV. Model Selection for multi-label classification
- V. Model Predictions
- VI. Conclusions & Perspectives



Problem Statement: Restaurants have thin margins







X Old School recipe/inventory management

500 Hrs/year on admin





No Big-Picture insights X Lack of data-driven

forecasts

Problem Statement: Restaurants have thin margins

Burnt Reimagining back of house operations





- Inventory demand forecast
- Automated inventory management
- Automated payment scheduling
- **G**Budgeting
- **S**Live food cost analysis
- **Posinegrations**
- Menu profitability
- GP Alerts

Problem Statement: Restaurants have thin margins

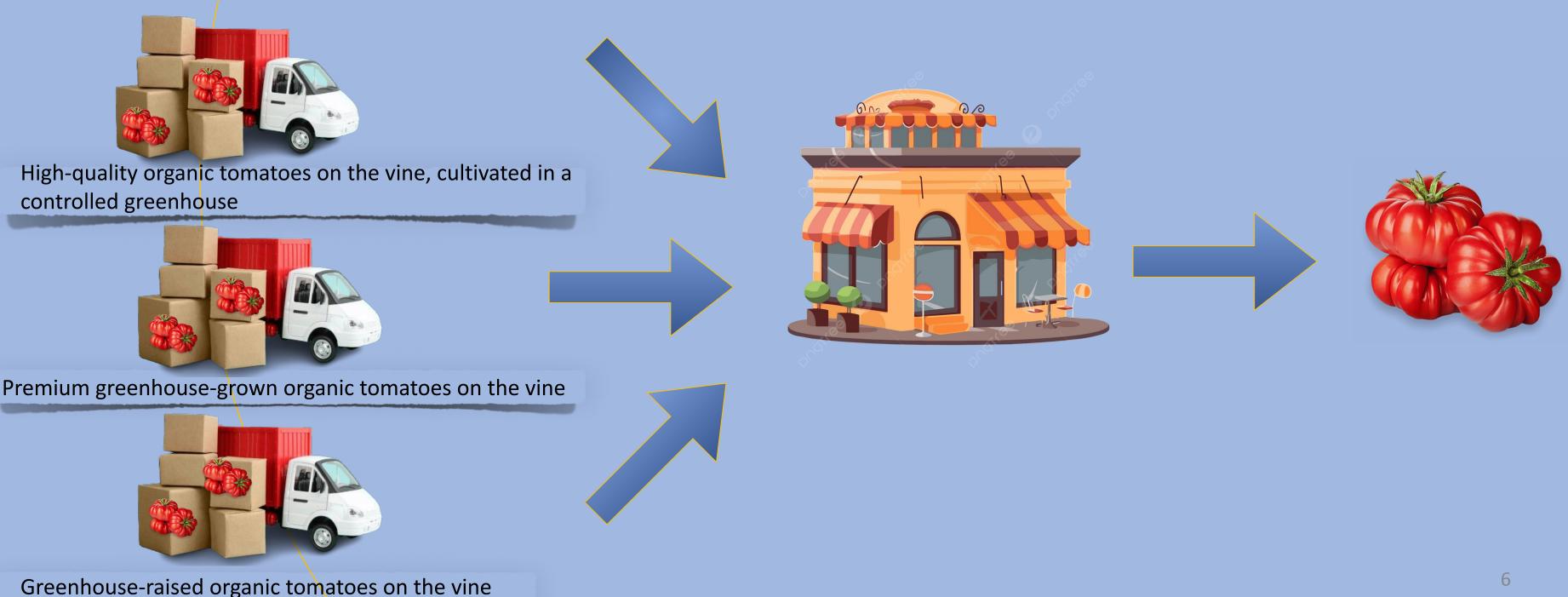
Burnt Reimagining back of house operations



- Inventory demand forecast
- Automated inventory management
- Automated payment scheduling
- **G**Budgeting
- Live food cost analysis
- **Posinegrations**
- Menu profitability
- GP Alerts

Problem Statement: Classifying Inventory Items

- Restaurants have on average 5-10 different suppliers with different ways to describing their products





Problem Statement: Multi-Label Classification



Laura's Lean Beef 92% Lean 8% Fat Ground Beef



American Foods 80/20 **Ground Beef**







Nestlé NESQUIK Chocolate Lowfat Milk Ready to Drink



NatureSweet Heavenly Salad Tomatoes

fairlife 2% Chocolate Ultra-Filtered Milk, Lactose Free



Produce organic Roma tomatoes

Food



• Food • Meat • Beef

Optimized search-bar engine

 Beverages • Non-alocholic • Dairy

Minimized wastage

Automated inventory management

• Fresh produce Tomato

Problem Statement: Approach

American Foods 80/20 Ground Beef

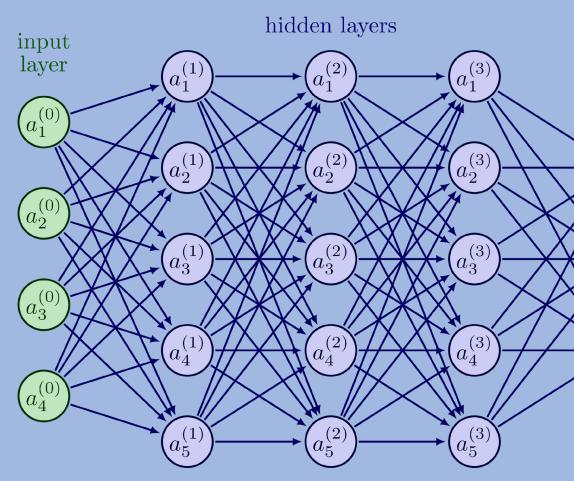
Laura's Lean Beef 92% Lean 8% Fat Ground Beef

fairlife 2% Chocolate Ultra-Filtered Milk, Lactose Free

Nestlé NESQUIK Chocolate Lowfat Milk Ready to Drink

> Produce organic Roma tomatoes

NatureSweet Cherubs Heavenly Salad Tomatoes



Fine-tuned LLMs







Beverages
 Non-alocholic
 Dairy

Food
Fresh produce
Fruits

Data Collection & Cleaning

- Need hierarchical categories
- Need labeled data
 - Scrape data from Instacart

product	label	Baked Goods
New Belgium Brewing Fat Tire Ale12 fl oz	alcohol/beer/ales/amber red ale	
Yuengling Beer, Traditional Lager, 24 Pack12 fl oz	alcohol/beer/ales/amber red ale	Dairy
George Killian's Irish Red Lager Beer12 fl oz	alcohol/beer/ales/amber red ale	Dang
Dragon's Milk Crimson Keep, Bourbon Barrel-Aged Red Ale, 11% ABV12 fl oz	alcohol/beer/ales/amber red ale	
Smithwick's Red Ale Beer14.9 fl oz	alcohol/beer/ales/amber red ale	Meat
Bell's Amber Ale12 fl oz	alcohol/beer/ales/amber red ale	
Alaskan Brewing Co. Amber12 fl oz	alcohol/beer/ales/amber red ale	Seafood
Alaskan Brewing Co. Beer, Alt Style Ale, Amber, 6 Pack12 fl oz	alcohol/beer/ales/amber red ale	
Classic Touch 3 Leaf Dish, Gold1 each	alcohol/beer/ales/amber red ale	Ready to Cook Meals
Karl Strauss Brewing Company Red Trolley Ale12 fl oz	alcohol/beer/ales/amber red ale	heady to Cook Medis

Alcohol	>	
Beverages	>	
Food	~	
Fresh Produce		
Frozen Food		(
Meat Alternatives		
Pantry		Ame
Deli		80% Grou 16 o
Baked Goods		
Dairy		1 [</td
Meat		2 3 4 5 6
Seafood		7 8 9 10 11



Food / Meat / Beef



erican Foods Group % Lean 20% Fat ound Beef DZ



Skylark Beef Liver, Sliced 16 fl oz



Laura's Lean Beef 92% Lean 8% Fat Ground Beef 16 oz

OCTYPE html> <html lang="en-US"> <title>Beef Products Delivery or Pickup Near Me | Instacart</title> <link href="https://www.instacart.com/categories/316-food/1807-meat/703-beef" rel="canonical"> k href="https://www.instacart.com/categories/316-food/1807-meat/703-beef?page=2" rel="next"> <meta content="Get Beef products you love delivered to you in as fast as 1 hour</pre> <meta content="Beef Products Delivery or Pickup Near Me | Instacart" property="og:title"> <meta content="https://www.instacart.com/categories/316-food/1807-meat/703-beef" property="og:url"> <meta content="Get Beef products you love delivered to you in as fast as 1 hour</pre> <meta content="width=device-width,initial-scale=1,user-scalable=yes" name="viewport">

Exploratory Data Analysis

- Uneven product distribution
- Some instances of mis-labeling



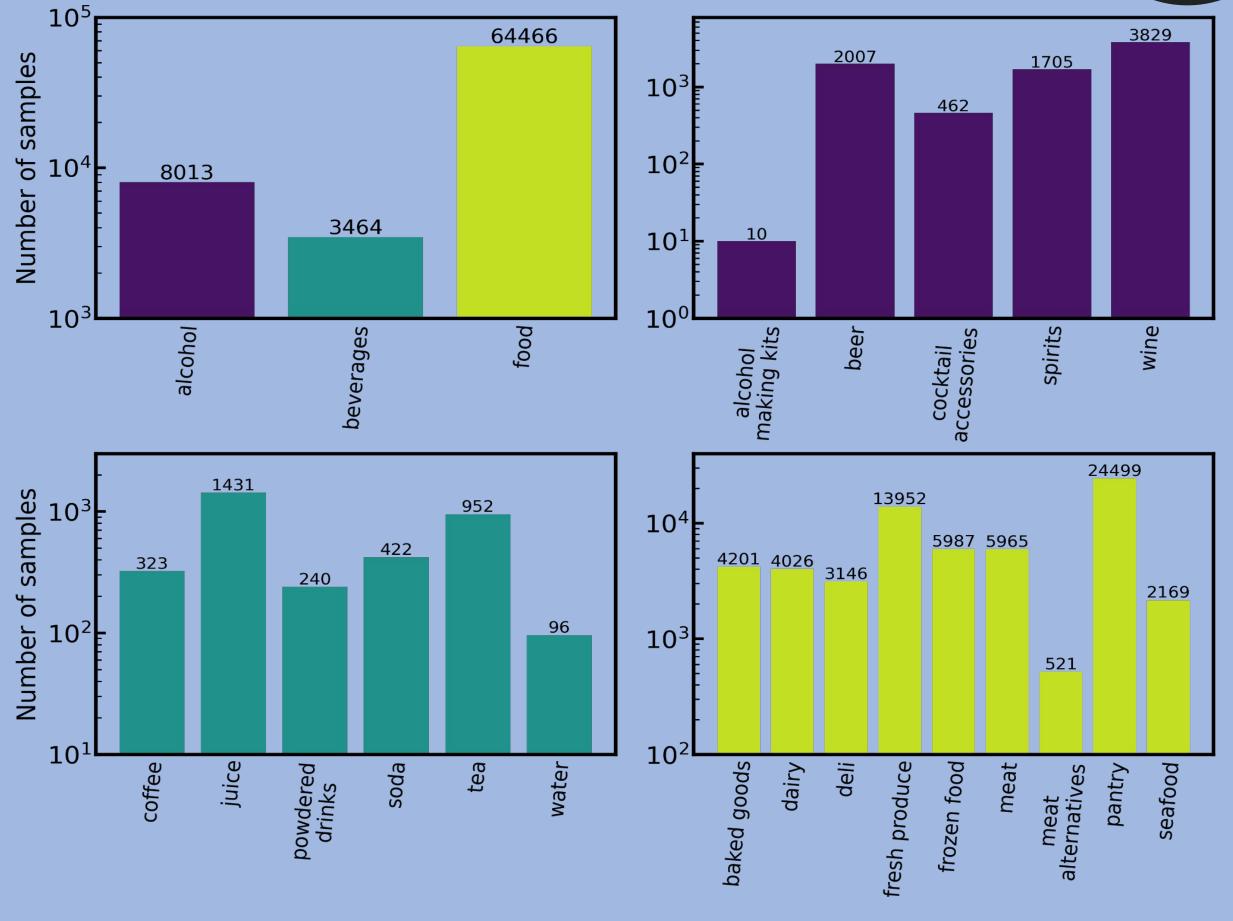
12 oz

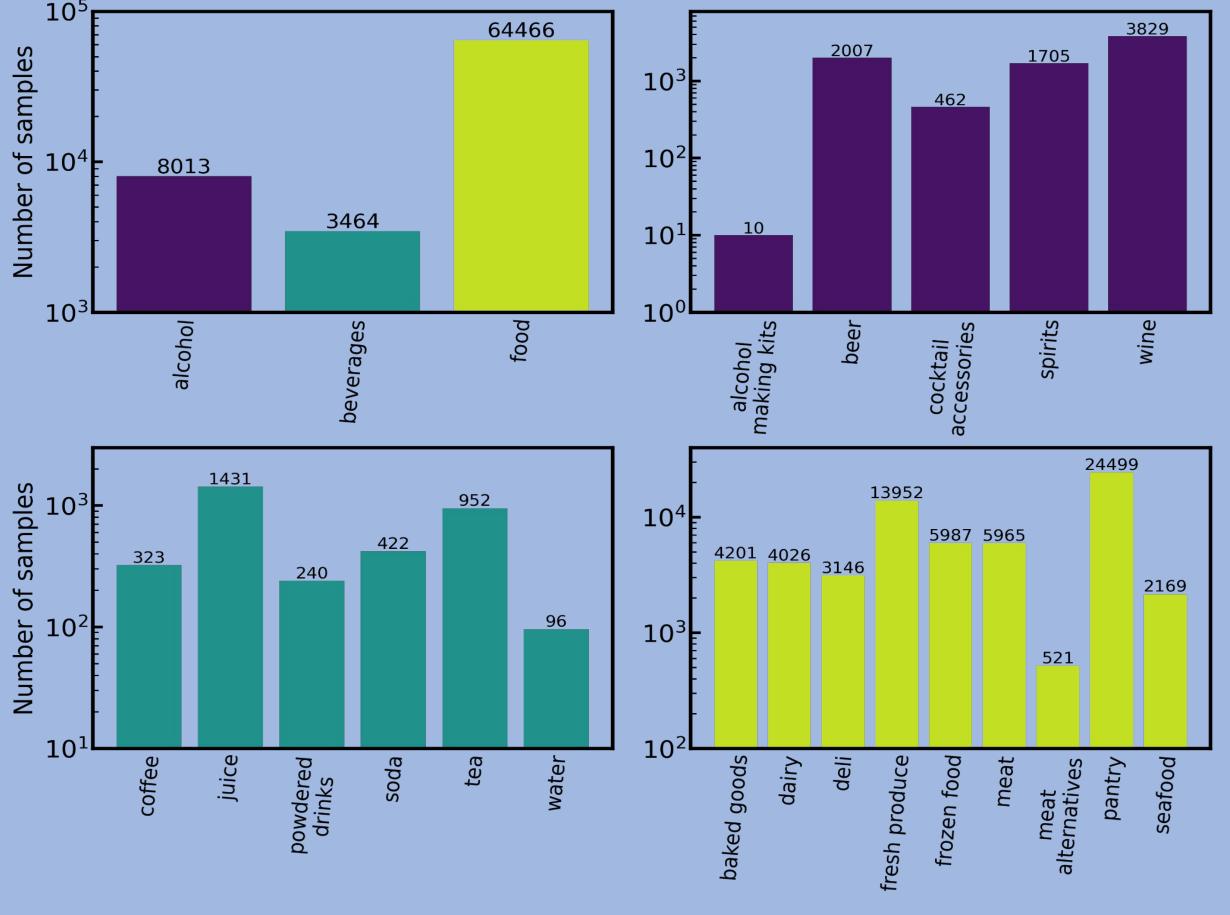
Fairway Pasta Organic Strozzapretiww 17.6 oz





RUBY GRAPEFRUIT each





Model Selection LLMs





OpenAl

GPT-2 (1.5 billion parameters)

Meta

Llama 2-7b-hf (7 billion parameters)

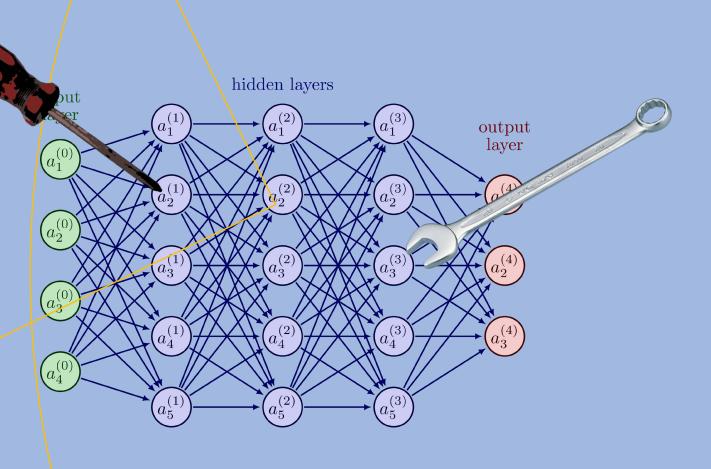
BERT (110 million parameters)

Google





Model Selection LLM finetuning

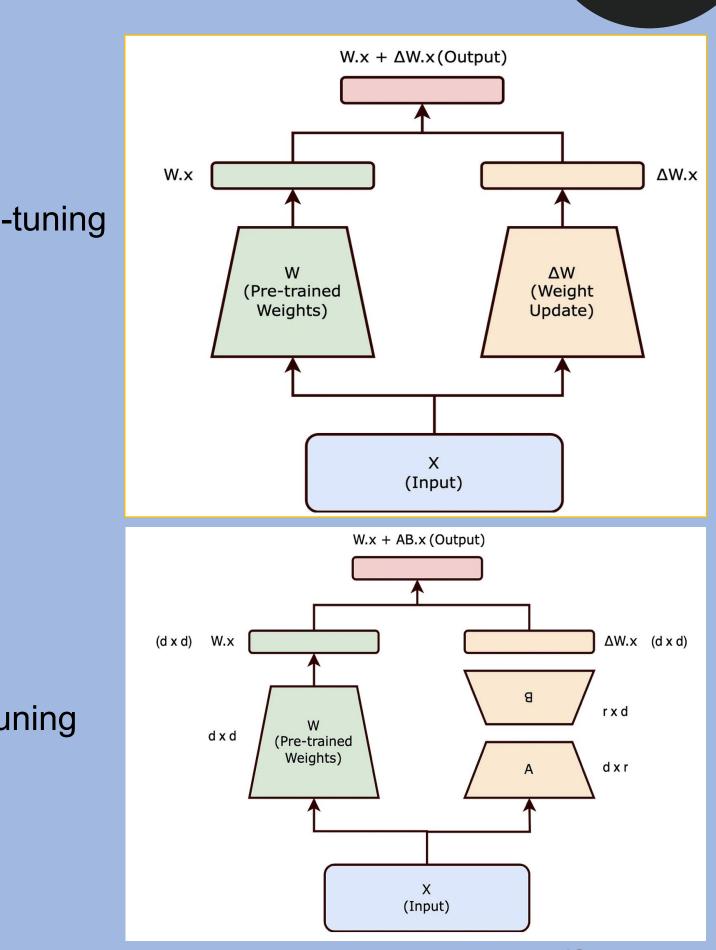


Traditional fine-tuning

Different approaches:

- Prompt fine-tuning
- Full parameter fine-tuning
- Partial parameter fine-tuning
- Adapter layers
- LoRA (low rank adaptation)

LoRA fine-tuning



Model Selection Llama finetuning

Llama-2: Auto-regressive language model with optimized transformers. Fine-tuning method:

Create a prompt to get category by autocompletion

Classify the text into food, beverages or alcohol and return the answer as the corresponding label. text: Signature Farms Tomatoes, Campari *label:*

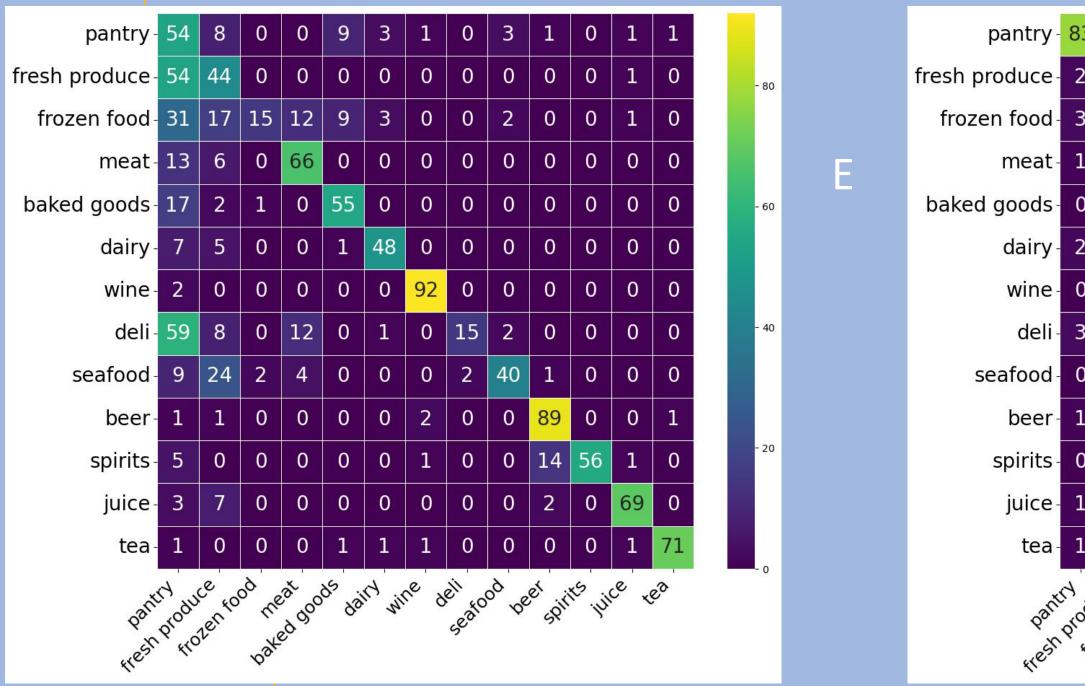
- Fine-tune using LoRA
 - Loss function: cross-entropy loss
 - Hyperparameters from literature

Qlora: Efficient finetuning of quantized Ilms. T Dettmers, A Pagnoni, A Holtzman, L Zettlemoyer. Advances in Neural Information Processing Systems, 2024



Model Selection Llama finetuning

- Base model



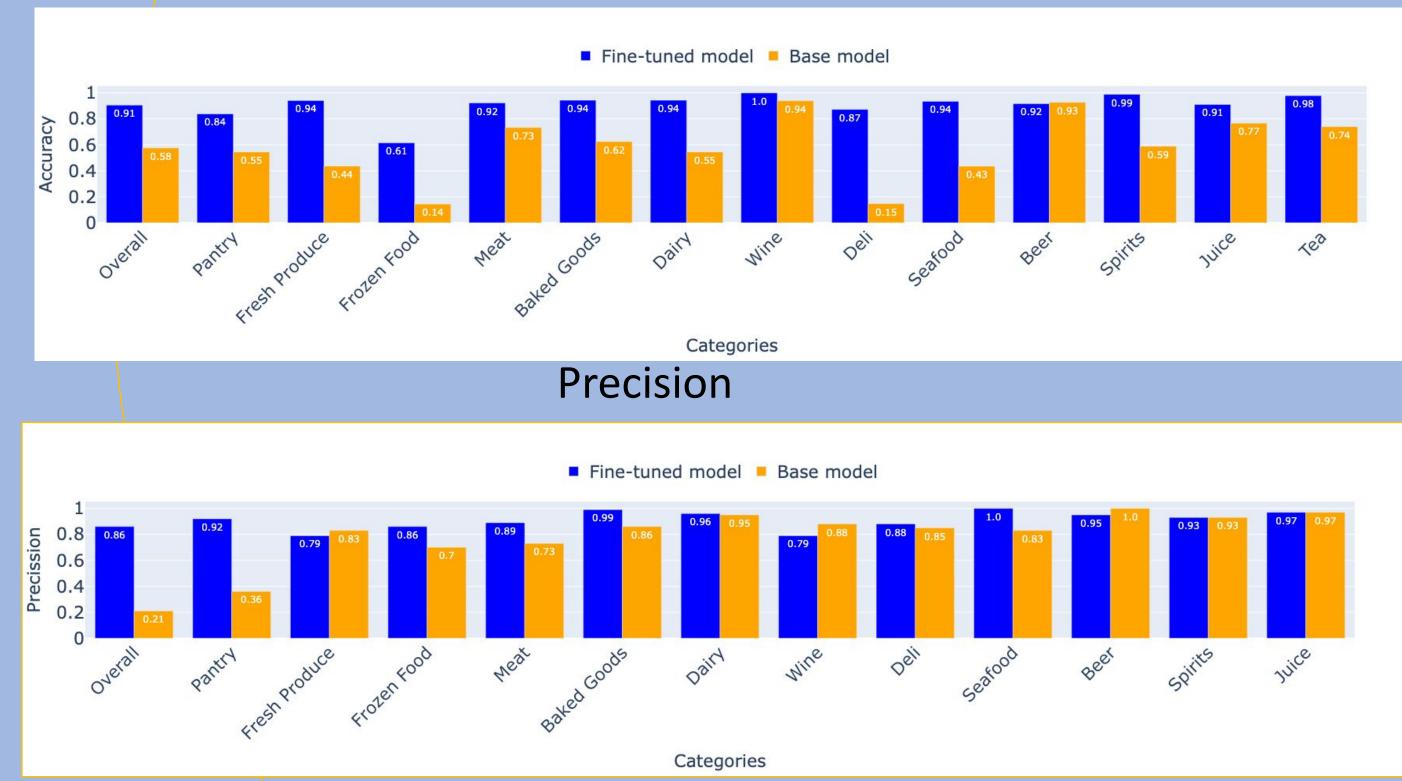


- Fine-tuned model

33	2	2	0	3	0	0	3	3	0	1	2	0			
2	95	3	0	0	0	0	1	0	0	0	0	0			
3	3	64	10	6	0	0	8	8	0	0	2	0		- 80	ê
1	0	2	83	0	0	0	4	0	0	0	0	0	2		
0	1	3	0	83	0	0	1	0	0	0	0	0	×		
2	0	0	0	0	83	0	2	0	0	0	0	0		- 60	
0	0	0	0	0	0	98	0	0	0	0	0	0			
3	1	4	3	0	1	0	89	1	0	0	0	0	4	- 40	Ê.
0	0	3	0	0	0	0	3	86	0	0	0	0			
1	0	0	0	0	0	3	0	0	88	1	2	1			
0	0	0	0	0	0	1	0	0	0	94	0	0	8	- 20	
1	1	0	0	0	0	0	1	0	0	3	82	2			
1	0	0	0	1	0	0	0	0	0	0	0	94			
20	.e0	odine	, at lo	des dai	rd with	e d	0 seato	ob ne	erspiri	rs jui	e' v	20		- 0	
, vo	len for	N.	2 ² 000	0.	1.		sed	v	જે.	Ÿ					
1.		A.												14	

Model Selection Llama finetuning

Accuracy





Model Selection Bert finetuning



- Create vectors to represent hierarchical categorization for each product
- Assign a unique number (label) to each unique vector
- Add a classification layer to the bert-base-cased model from HF

product	label	lab_0	lab_1	lab_2	lab_3	lab_4	lab_5	base_label
New Belgium Brewing Fat Tire Ale12 fl oz	alcohol/beer/ales/amber red ale	0	1	0	0	0	0	1
Bud Light Hard Seltzer Iced Tea Variety Pack, Slim12 fl oz	alcohol/beer/beer variety packs	0	1	1	0	0	0	23
Guastaferro Taurasi Primum Riserva750 ml	alcohol/wine/red wine/aglianico	0	4	5	1	0	0	196
Signature SELECT Blue Cheese Crumbles5 oz	food/dairy/cheese/blue cheese	2	1	0	3	0	0	335
Driscoll's Organic Blackberries6 oz	food/fresh produce/fresh fruit/berries/blackberries	2	3	0	5	0	0	1410

orization for each product e vector cased model from HF

Model Selection Bert/finetuning



0.00

0.01

0.00

1.00

0.00

0.00

soda

0.00

0.00

0.07

0.00

0.96

0.00

tea

0.00

0.02

0.00

0.00

0.00

1.00

water

403

396

3

р

579

45

alterr

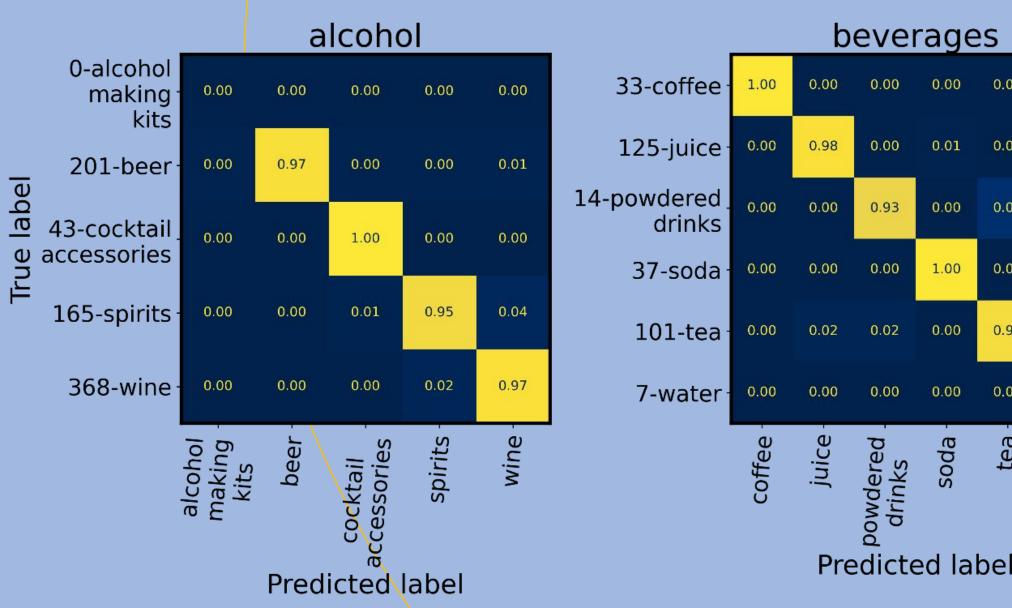
2483-

209-se

1348

657-froze

• Excellent performance for the two top levels



All Products (test)

										_			
				80	0-a	lcol	nol [.]		0.97		0.01		0.02
		True label	33	0-b	eve	erag	Jes ⁻		0.01		0.96		0.03
		·		6	465	5-fo	od		0.00		0.00		1.00
								જે	cohol		beverat	ner N	400d
				f	000	Ч			F	² re	dicted	lat	bel
-baked	0.93	0.02	0.01	0.01			0.00	0.01					
goods 6-dairy				0.08									
30-deli			1										
8-fresh roduce													
en food													
9-meat		0.00	0.00	0.02	0.00	0.94	0.00	0.03	0.01				
5-meat natives	0.00	0.00	0.00	0.02	0.02	0.00	0.93	0.02	0.00				
pantry	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.96	0.00				
eafood	0.00	0.00	0.00	0.04	0.00	0.02	0.00	0.03	0.90				
	baked goods	- dairy		produce	froze		m altern	pantry -	seafood -			17	
	Predicted label												

Model comparison GPT2(1.5 billion) Vs Bert-Uncased (110M parameters)

0.8

0.6

0.4

0.2

Label

Irue

Normalized Confusion Matrix

Normalized Confusion Matrix

0.0

0.0

0.0

0.0

0.0

0.01

0.0

0.0

0.01

0.0

0.01

0.9

beer

pantry

frozen food

fresh produce

seafood

meat

dairy

deli

juice

wine

spirits

beer

baked goods

0.0

0.0

0.0

0.0

0.0

0.0

0.0

0.0

0.01

0.92

0.03 0.03

Spirits

0.02 0.02

0.0

0.0

0.0

0.0

0.0

0.0

0.0

0.0

0.98

0.05

0.0 0.0 0.0 0.0 0.0	0.01 0.0 0.0 0.0	0.0 0.01 0.0 0.0	0.01 0.0 0.01 0.0	0.0 0.0 0.0	0.1 0.14 0.03	0.13 0.15 0.03	0.05 0.04 0.01	0.0 0.04 0.02	0.01 0.03 0.01	0.03 0.01 0.79	0.01 0.48 0.03	0.65 0.09 0.08
0.0 0.0	0.0 0.0	0.0	0.01	0.0								
0.0	0.0				0.03	0.03	0.01	0.02	0.01	0.79	0.03	0.09
		0.0	0.0					0.02	0.01		0.05	0.08
0.0				0.01	0.04	0.03	0.01	0.0	0.86	0.01	0.01	0.01
	0.0	0.0	0.0	0.0	0.11	0.0	0.01	0.83	0.01	0.01	0.03	0.0
0.0	0.0	0.01	0.01	0.0	0.0	0.02	0.95	0.0	0.0	0.0	0.01	0.0
0.0	0.0	0.0	0.0	0.01	0.0	0.86	0.04	0.0	0.01	0.0	0.01	0.07
0.01	0.0	0.0	0.0	0.0	0.71	0.05	0.06	0.03	0.04	0.03	0.01	0.05
0.0	0.01	0.0	0.0	0.96	0.0	0.01	0.01	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.02	0.95	0.01	0.0	0.0	0.0	0.0	0.0	0.01	0.0	0.01
0.0	0.01	0.99	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.03	0.9	0.07	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.01	0.0
0.89	0.04	0.01	0.03	0.0	0.0	0.01	0.01	0.0	0.0	0.0	0.0	0.0
beer	Spirit	wine	Juice	tea	deli	baked	d an dairy	meat	Searo	fresh	Proze,	pan n fo
	0.0 0.01 0.0 0.0 0.03 0.89	0.0 0.0 0.01 0.0 0.0 0.01 0.0 0.01 0.0 0.01 0.03 0.9 0.89 0.04	0.00.00.00.010.00.00.010.010.00.010.010.020.020.010.990.030.940.01	0.00.00.00.00.010.000.00.00.010.010.020.020.010.020.950.020.010.990.030.940.070.890.040.01	0.00.00.00.010.010.00.00.00.00.010.010.000.000.960.010.020.950.010.030.990.070.000.890.040.010.030.02	0.00.00.00.00.010.00.010.000.000.000.000.710.010.010.000.000.960.000.010.010.020.950.010.000.030.990.020.000.000.010.890.040.010.030.000.01	0.0 0.0 0.0 0.01 0.0 0.86 0.01 0.00 0.00 0.01 0.71 0.05 0.01 0.01 0.00 0.96 0.71 0.05 0.01 0.01 0.01 0.96 0.96 0.01 0.01 0.01 0.01 0.02 0.95 0.91 0.01 0.01 0.01 0.01 0.01 0.99 0.95 0.01 0.01 0.01 0.01 0.02 0.95 0.91 0.91 0.91 0.91 0.91 0.91 0.03 0.01 0.99 0.02 0.90 0.01 0.91 0.91 0.03 0.99 0.02 0.90 0.90 0.91 0.91 0.91 0.89 0.94 0.91 0.93 0.90 0.90 0.91 0.91	0.0 0.0 0.0 0.01 0.0 0.86 0.04 0.01 0.0 0.0 0.01 0.05 0.06 0.01 0.01 0.00 0.00 0.01 0.01 0.01 0.01 0.01 0.02 0.95 0.01 0.01 0.01 0.01 0.01 0.01 0.02 0.05 0.01 0.01 0.01 0.01 0.01 0.01 0.02 0.01 0.01 0.01 0.01 0.01 0.02 0.04 0.01 0.03 0.01 0.01 0.01 0.01	0.0 0.0 0.0 0.0 0.0 0.86 0.04 0.0 0.01 0.0 0.0 0.0 0.01 0.05 0.06 0.03 0.01 0.01 0.01 0.01 0.01 0.01 0.01 0.01 0.01 0.01 0.01 0.02 0.95 0.01 0.01 0.01 0.01 0.01 0.01 0.01 0.02 0.95 0.01 0.01 0.01 0.01 0.01 0.01 0.03 0.01 0.07 0.01 0.02 0.01 0.01 0.01 0.01 0.03 0.04 0.01 0.03 0.01 0.01 0.01 0.01 0.01	0.0 0.0 0.0 0.01 0.08 0.04 0.0 0.01 0.01 0.00 0.01 0.02 0.02 0.071 0.05 0.06 0.03 0.04 0.01 0.01 0.02 0.01 0.01 0.05 0.06 0.03 0.04 0.01 0.01 0.01 0.02 0.02 0.02 0.01 0	0.0 0.0 0.0 0.0 0.01 0.00 0.866 0.04 0.00 0.01 0.00 0.01 0.00 0.00 0.01<	0.0 0.0 0.0 0.0 0.0 0.86 0.04 0.0 0.01 0.0 0.01 </td

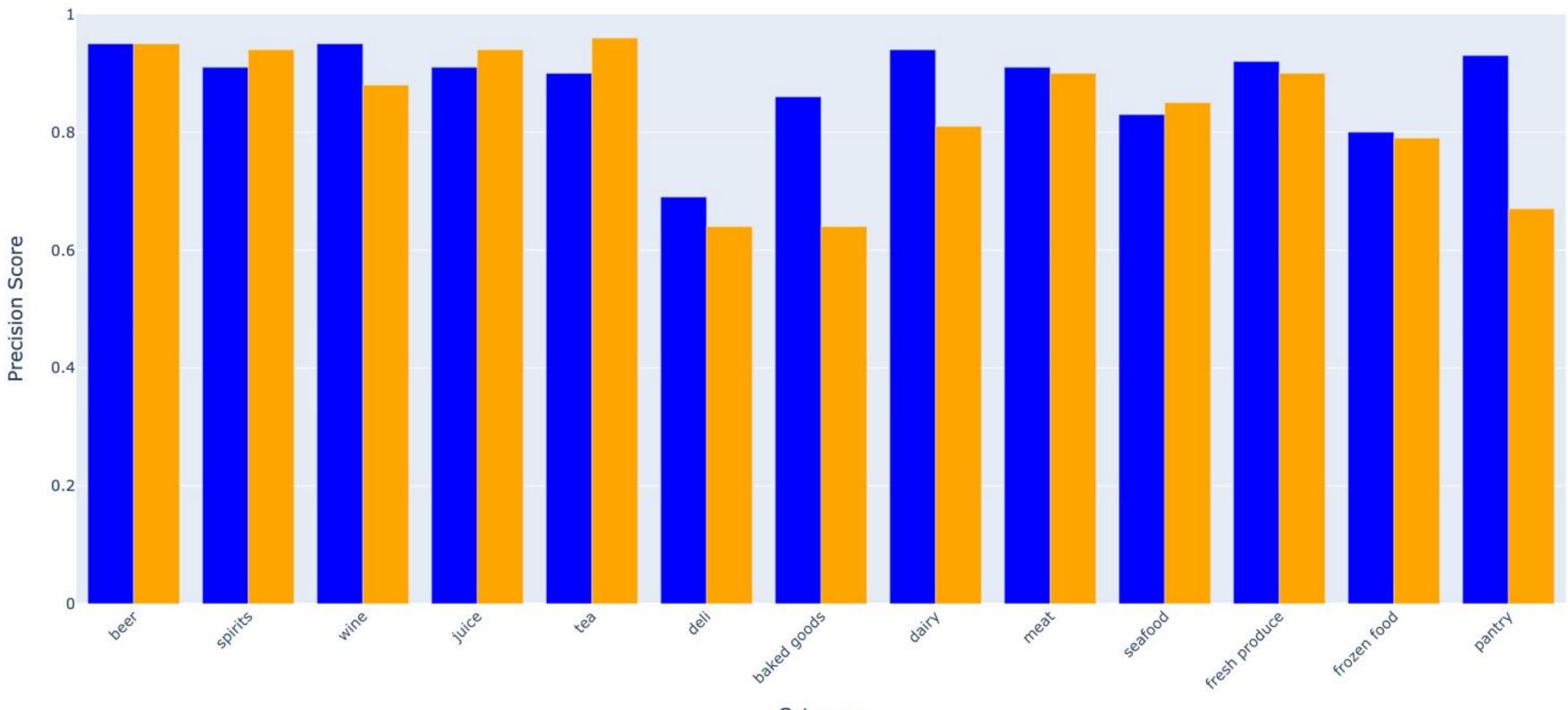
Predicted Label

-at	hood	Pro Pro

Label True

0.0	0.0	0.01	0.01	0.0	0.0	0.0	0.03	0.01	0.93	1	
0.0	0.01	0.04	0.04	0.01	0.05	0.03	0.04	0.72	0.07		
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.94	0.01	0.04	0.8	8
0.0	0.0	0.02	0.0	0.0	0.0	0.88	0.01	0.05	0.04		
0.0	0.0	0.03	0.0	0.0	0.92	0.0	0.0	0.03	0.01	0.6	6
0.0	0.01	0.01	0.0	0.93	0.0	0.0	0.01	0.01	0.03		
0.0	0.0	0.02	0.88	0.01	0.0	0.0	0.0	0.03	0.05		
0.0	0.0	0.68	0.01	0.01	0.06	0.02	0.03	0.08	0.11	0.4	4
0.02	0.9	0.0	0.01	0.0	0.0	0.0	0.01	0.01	0.02		
0.98	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.01	0.2	2
0.05	0.0	0.0	0.0	0.01	0.0	0.0	0.0	0.01	0.0		
0.03	0.02	0.0	0.01	0.01	0.0	0.0	0.01	0.0	0.0	0	
Wine	Juice	deli	baked	dairy 900ds	meat	Searo	fresh	frozei Produce	Pantry n food		
			Predicte								

Precision Scores by Category for GPT-2 and BERT Uncased Models



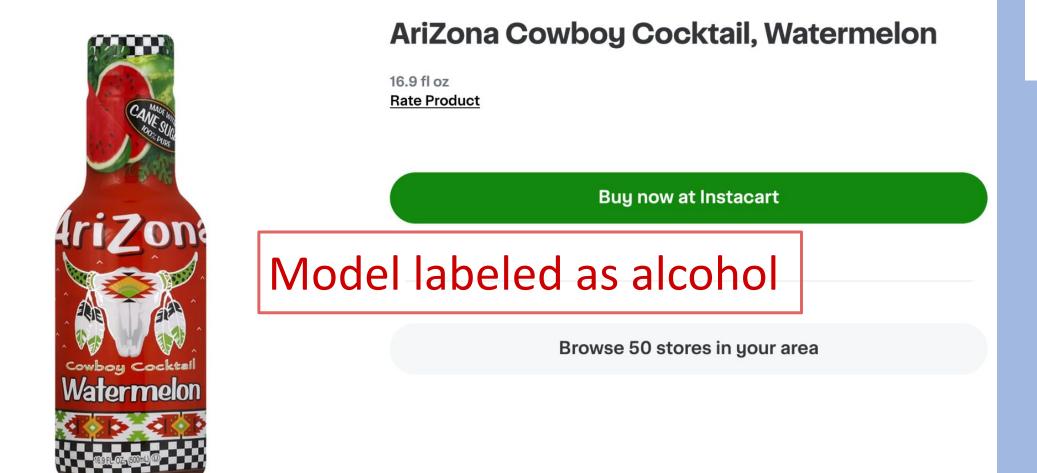
Category



Common model issues

- Caught a few mislabeled products
- Mostly confused hard-to-label products

Beverages > Juice > Fruit Juice > Watermelon Juice



Beverages > Tea > Leaf Tea > Tea Blends

- Mislabeled

Model labeled correctly as food



Conclusions & Perspectives

- Key findings:
- Successfully categorized products with different open source LLMs.
- Implemented efficient approaches of fine tuning.
- Identified some mis-labeled cases in the existing labelled dataset (from Instacart)
- Gained insights into improving classification models by investigating mis-classified products

Conclusions & Perspectives

Future perspectives:

- Deeper hierarchical classification
 - Need more data
 - Define a loss that takes the hierarchical structure into account
- Combine insights from the two projects to build a personalized

Al-assistant for each restaurant's business analytics

THANK

Davood B. Dar Student at Rutgers University



Burnt Hugginface Instacart



Evaristo Villaseco Arribas PhD in Physics at Rutgers University



ACKNOWLDEGEMENTS:



Amir Kazemi-Moridani, PhD Astrophysicist | Data Scientist

