Doctoral Dissertation | Revathy Venkataramanan
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Explainable Process Recommendation Through Multi-Contextual Grounding of Dynamic Multimodal Process Knowledge Graphs

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Can I eat this food or not? Why?

Recipe Text
Peel potatoes, then cut them into thin strips.Heat oil in a deep fryer or skillet. Wait till the oil reaches desired temperature for deep frying. Then fry the potatoes in batches until golden brown and crispy. Mix salt and pepper in a large bowl...

Domain Knowledge
+ Disease Context
+ Nutrition
+ Cooking method effects

Recommender

Observed or Past data
Recipes text and image

Ingredients
- Potato → Recommend / Avoid
- Canola Oil → Recommend / Avoid
- Salt → Recommend / Avoid
- Pepper → Recommend / Avoid

Cooking Methods
- Peel
- Cut
- Deep fry → ? → Recommend / Avoid
- Toss

Interactions
- Potato + Deep Fry → ? → Recommend / Avoid
- Oil + Deep Fry → ? → Recommend / Avoid

Recommenation: Caution

Explanations

Potato - Healthy CHO, High GI [WebMd]

Canola Oil - unrefined, good fat [WebMD]

Deep frying - Trans Fat [USFDA]

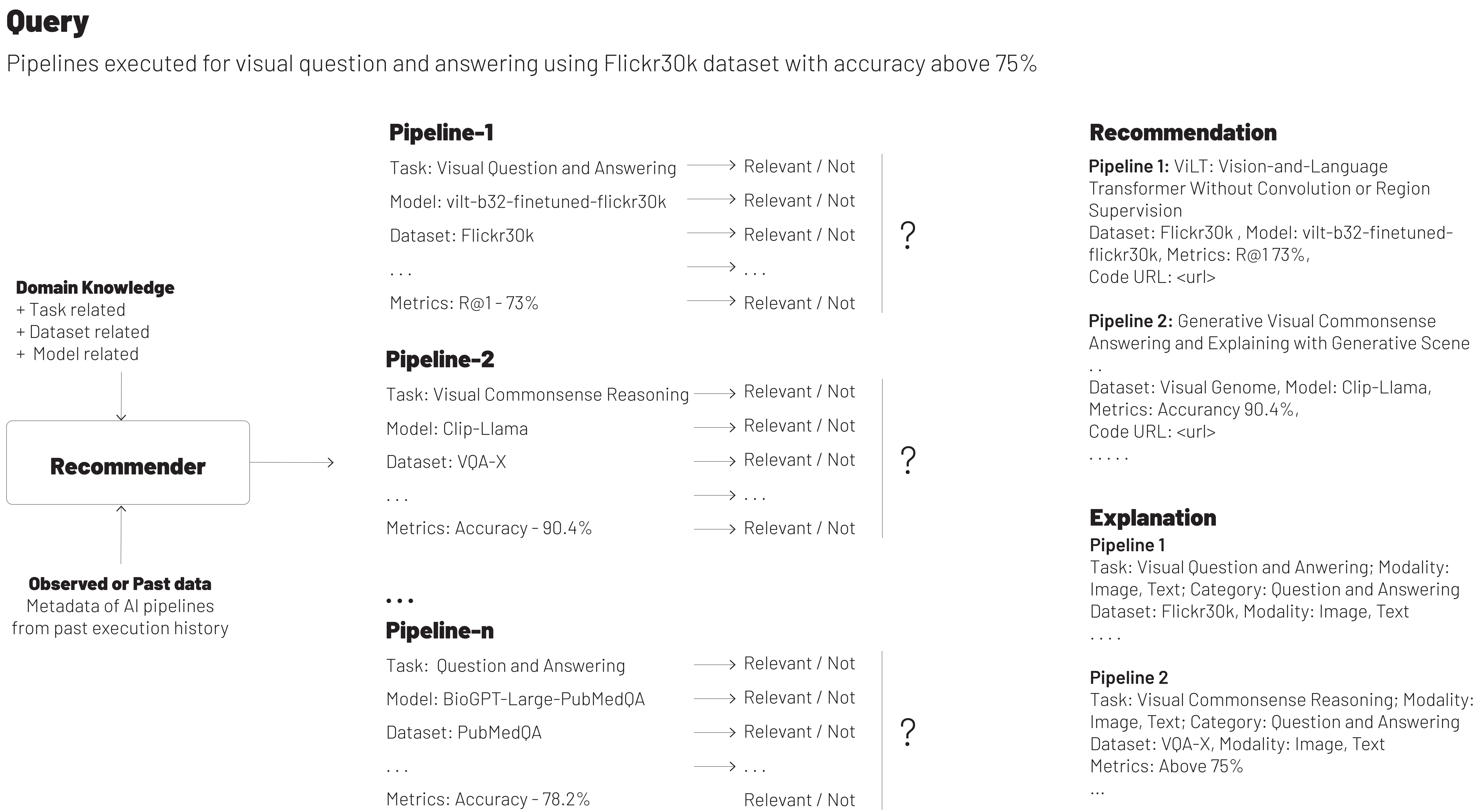
Potato + frying - Vitamin A&C loss [USFDA]

Allergens - dairy free, nut free

DV Calories - within limit

Compositional Reasoning

Which AI pipeline is best suited for a given task and dataset?


Query
Pipelines executed for visual question and answering using Flickr30k dataset with accuracy above 75%
Domain Knowledge
+ Task related
+ Dataset related
+ Model related
Recommender
Observed or Past data
Metadata of AI pipelines
from past execution history
Pipeline-1
Task: Visual Question and Answering
Model: vilt-b32-finetuned-flickr30k
Dataset: Flickr30k
. . .
Metrics: R@1 - 73%
Relevant / Not
Relevant / Not
Relevant / Not
. . .
Relevant / Not
?
Pipeline-2
Task: Visual Commonsense Reasoning
Model: Clip-Llama
Dataset: VQA-X
. . .
Metrics: Accuracy - 90.4%
Relevant / Not
Relevant / Not
Relevant / Not
. . .
Relevant / Not
?
. . .
Pipeline-n
Task: Question and Answering
Model: BioGPT-Large-PubMedQA
Dataset: PubMedQA
. . .
Metrics: Accuracy - 78.2%
Relevant / Not
Relevant / Not
Relevant / Not
. . .
Relevant / Not
?
Recommendation
Pipeline 1: ViLT: Vision-and-Language Transformer Without Convolution or Region Supervision
Dataset: Flickr30k , Model: vilt-b32-finetuned-flickr30k, Metrics: R@1 73%,
Code URL: <url>
Pipeline 2: Generative Visual Commonsense Answering and Explaining with Generative Scene
. .
Dataset: Visual Genome, Model: Clip-Llama, Metrics: Accurancy 90.4%,
Code URL: <url>
. . . . .
Explanation
Pipeline 1
Task: Visual Question and Anwering; Modality: Image, Text; Category: Question and Answering
Dataset: Flickr30k, Modality: Image, Text
. . . .
Pipeline 2
Task: Visual Commonsense Reasoning; Modality: Image, Text; Category: Question and Answering
Dataset: VQA-X, Modality: Image, Text
Metrics: Above 75%
...

What is needed?

01. Structured Process Data

Structured data that explicitly represents the interactions of entities present in the processes

02. Multi-contextual Knowledge

Knowledge from multiple contexts to derive meaningful insights, leading to enhanced analysis of the process entities

03. Methods for Process Recommendation

Process recommendation methodologies that involves compositional reasoning to perform collective inferencing

04. Explainations for Recommendation

Given high-stake domains, explainable and traceable recommendations are essential (traceability: resons and explanations traced back to trusted source)

Challenges

01. Unstructured Data

Unstructured data in natural language format lacking explicit entities invovled and their interactions

02. Lack of Knowledge

The data consists of low-level information without context or domain-specific knowledge, limitng the ability to derive meaningful insights

03. Explainable Process Recommendation

Unlike item recommendation where relevance of a single item is evaluated, process recommendation need to collectively evaluate multiple items. Given high-stake domains, user-level explanations are essential

04. User Acceptance of Explanations

The user should find the explanations relevant, clear and trustworthy

Existing Works

Existing works on process recommendation

Word Similarity

Node Prediction: Most process recommendation work aims for node prediction [1],

Vector Embeddings: A few works even reduced the problem to word prediction using vector embeddings [2]

TF-IDF: Liu et al., using ontology for task definition and TF-IDF to identify similar tasks to user's history [4]

Behaviourial Similarity

A* Algorithm Dong et al., used A* algorithm with pruning to rank process models based on behavioral similarity [3]

Behavior: Traces of process stage executions. Eg: <f1, ..f3,..fn>, <f2,...f4,.. fn> [11,12]

Graph Similarity

Natural language: Text information on the nodes and node embeddings [13, 6,7]

Graph Structure: Largest common subgraph between two process [8]

Graph Distances: Cophenetic distance, Graph edit distance, Graph isomorphism [9, 10]

Challenges still remain...

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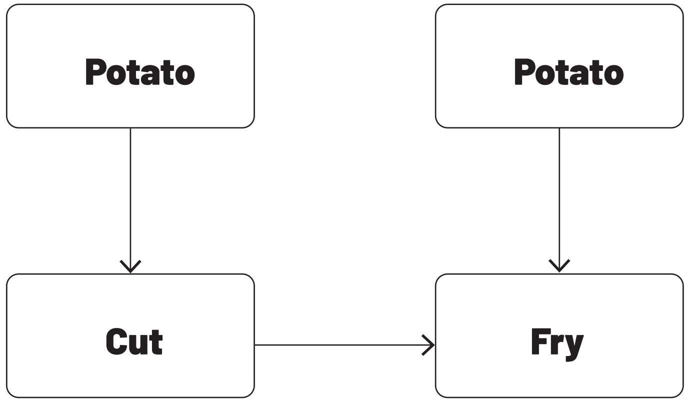
01.

Natural Language Text
Peel potatoes, then cut them into thin strips.Heat oil in a deep fryer or skillet. Then fry the potatoes in batches until golden brown and crispy. . .

02.

Entites
Ingredients: potato, oil, salt, pepper
Cooking actions: peel, cut, fry, season

03.



RQ1

Can the process entities be extracted from unstructured data with limited ground truth data?

High level knowledge

Caution | Recommend

Greater than 70
High Glycemic Index | Carb: Fibre >= 10:1
Healthy Carbohydrate

Glycemic index: 78 | Carb: 37g, Fibre: 4g

Potato

Low level data

RQ2

How can process entities be elevated to high-level concepts and represented in a structured format with multimodal data for reasoning?

RecipeText
Peel potatoes, then cut them into thin strips. Heat oil in a deep fryer or skillet. Then fry the potatoes in batches until golden brown...

Explainable Recommendation

Can I eat this food? Caution

Explanations
Potato - Healthy CHO, High GI [WebMd]
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Deep frying - Trans Fat [USFDA]
Potato + frying - Vitamin A&C loss [USFDA]
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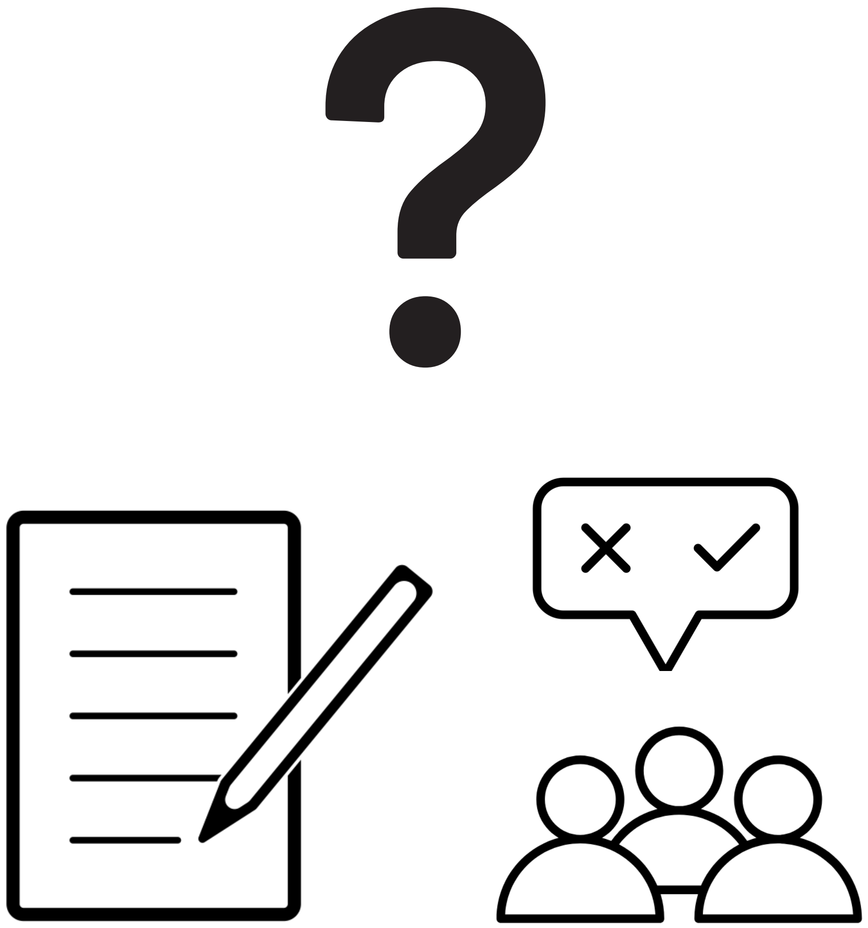
RQ3

How can explainable recommendation results be produced that are supported by reasoning and can be traced back to trusted sources?



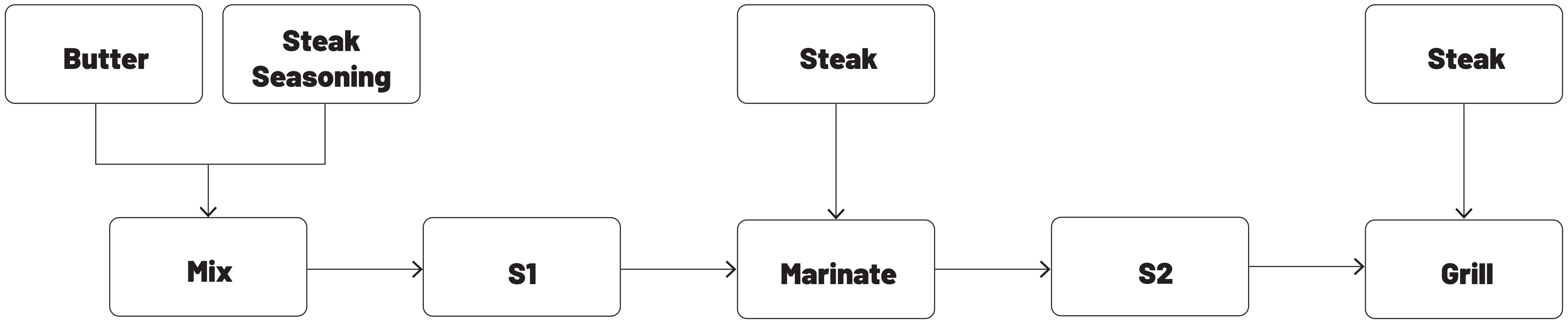
RQ4

Do the users accept the explanations given by the system interms of clarity, relevance, trustworthiness and format?

Thesis Statement

A neurosymbolic approach for explainable process recommendation through multi-contextual grounding of dynamic multimodal process knowledge graphs to enable reasoning and traceability for enhanced recommendation and trustworthiness.

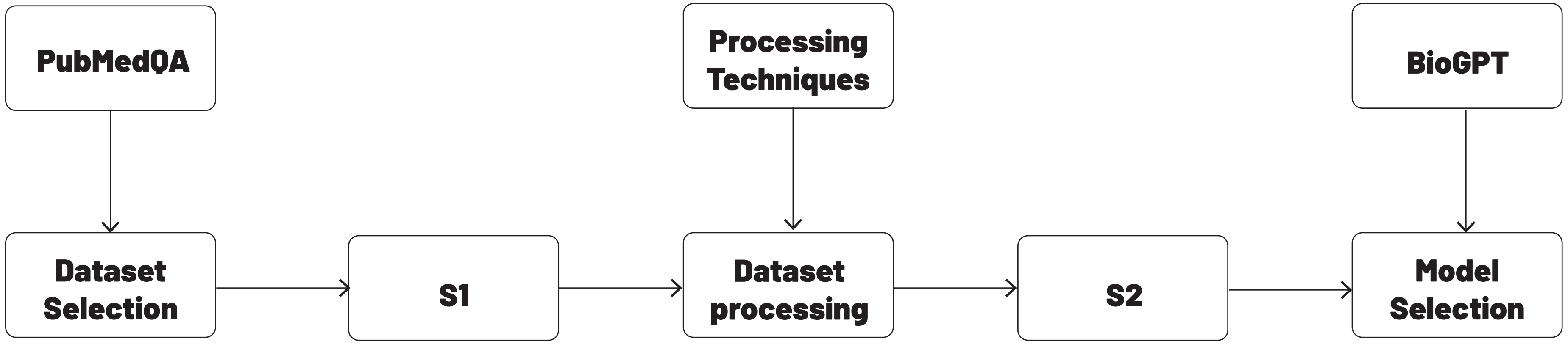
Process Graphs



Cooking Process Graph

Entities

Artifacts: Ingredients
Actions: Cooking Methods

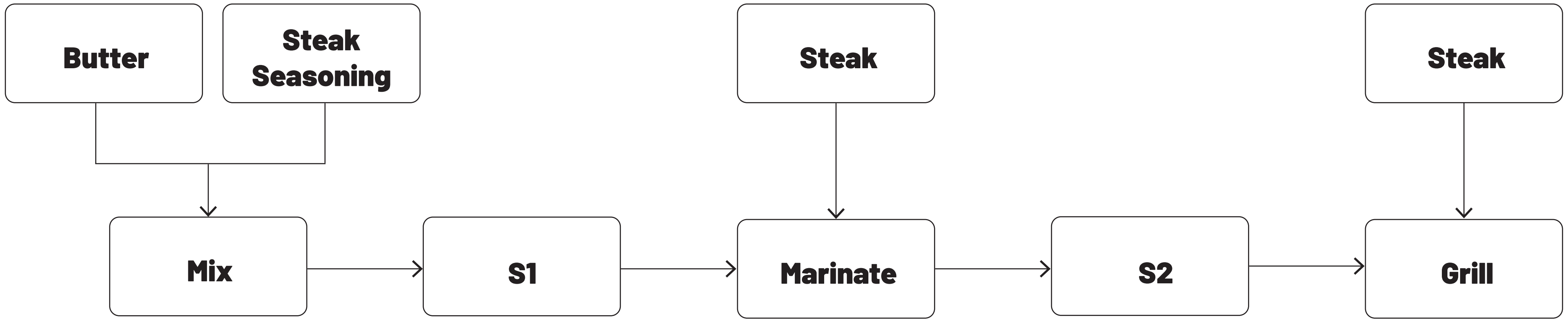


AI Pipeline Process Graph

Entities

Artifacts: Dataset, Model, Metrics
Actions: Dataset selection, Model training

Cooking Process Knowledge Graphs



Multi-contextual Grounding

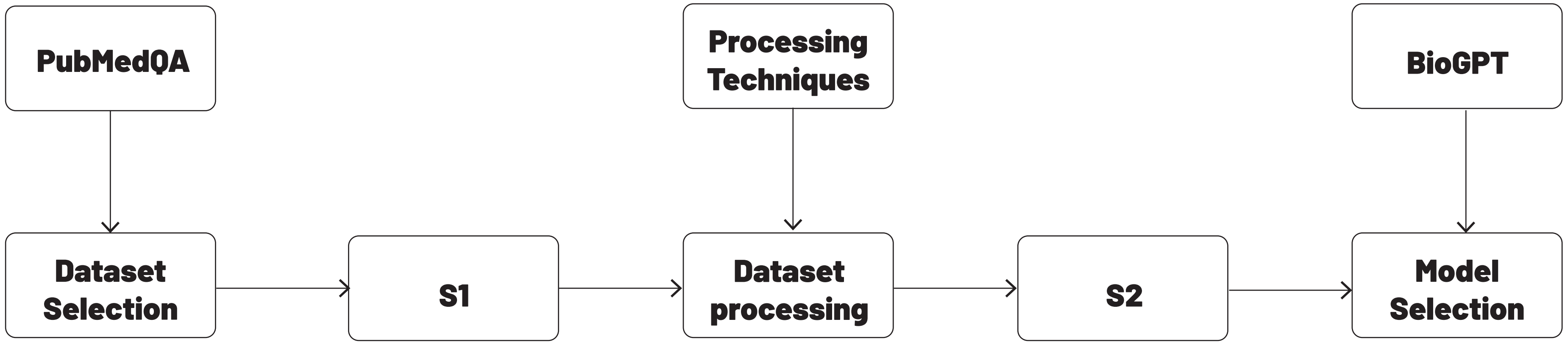
Butter
Category: Dairy Fat
Smoke point: 395F
Diabetes label: Unhealthy, Saturated fats
Nutrition: Carb:0g, fat: 11g

Steak
Category: Red Meat, Pork
Diabetes label: Unhealthy, red meat
GI: 0
Nutrition: Carb: 0g, Choles: 17g

Rules
Direct heat + meat —> Carcinogens
Fat + above smoke point —> Free radicals
Red Meat —> related to colorectal cancer
Meat&Seafood —> Above 165F
High-Temp + Starch —> Acrylamide

Steak + Grill
Nutri Ret: Vit-B: 90%,...
Carcinogens: PCA, HCA
Safe temperature: 165F

AI Pipeline Process Knowledge Graphs



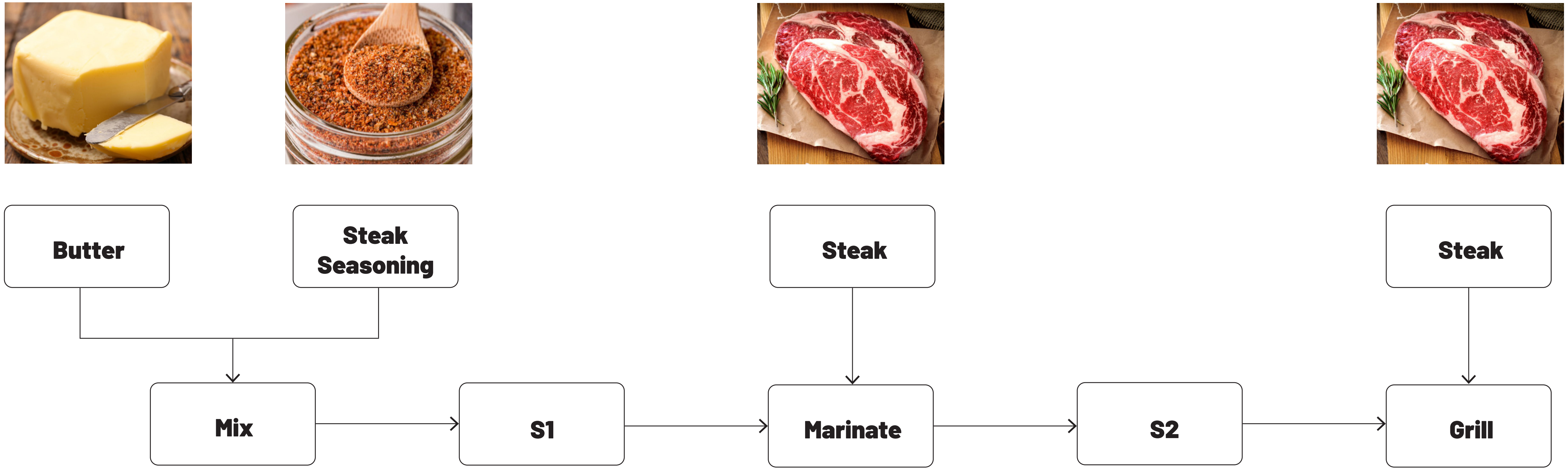
Multi-contextual Grounding

Task
Question and Answering
Modality: Text
Category: Generation
Description: Question and Answering task trains the models to retrieve answers to given questions

Dataset
PubmedQA
Modality: Text
Task category: Question and answering, text generation
Description: PubMedQA is a question and answering dataset on clinical research questions.

Model
BioGPT-Large-PubMedQA
Model Type: Llama
Description: a domain-specific generative Transformer A domain-specific language model pre-trained on large-scale biomedical literature.

Multimodal data for Recipes



Multimodal data for AI pipelines

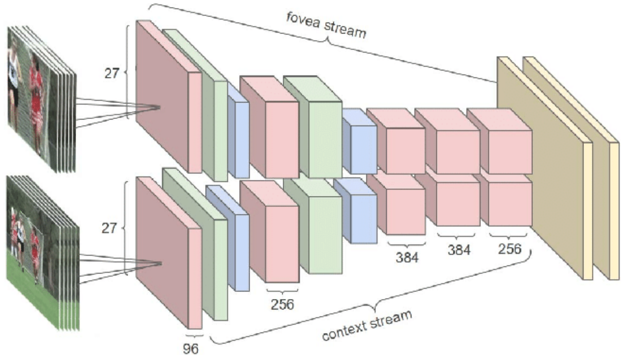
Document PDF

Numerical

Metrics
Accuracy: 96%
R@1: 95%

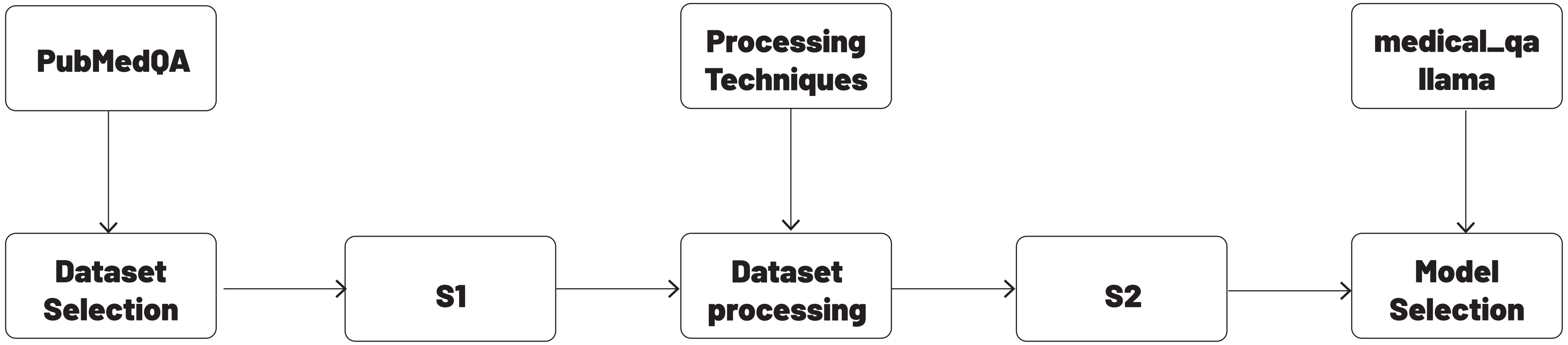
Embeddings

Embeddings of node names and descriptions as they are good at approximations



Images

Figures in the documents or reports



Outline

Explainable Recipe Recommendation

RQ1. Entity Extraction using limited ground truth data

RQ2. Elevating process entities to high-order concepts and a structured representation

RQ3. Explainable recipe process recommendation

RQ4. User Acceptance of Explanations given by the model

Explainable AI Pipeline Recommendation

RQ1. Entity Extraction using limited ground truth data

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Explainable Recipe Recommendation for Diabetes

Why Food Recommendation?

Manage Chronic Diseases
Diet plays a major role in management of chronic diseases. Several studies show that diabetes can be managed well through proper diet management

Multiple Components
One of the challenges is that one needs to analyze multiple components such as ingredients, cooking methods, nutrition, calorie content and etc to analyze a given recipe

Scattered Guidelines
The guideline information for diabetes is scattered across multiple sources. One of the studies reported that 33% of the patients did not follow diet due to lack of readily available information, the second highest cause.

Tedious day to day task
Analysing multiple components by bringing information from multiple sources on a daily basis is a tedious task, especially when the food is in front of you

Existing Work

Non Adherence to Medical Guidelines
Existing meal recommender systems do not focus on disease specific analysis and do not strictly adhere to medical guidelines

Cooking Methods
In general, cooking methods were not considered explicitly as a part of their meal analysis plan. Most works focus on calorie content, nurtiion and ingredients

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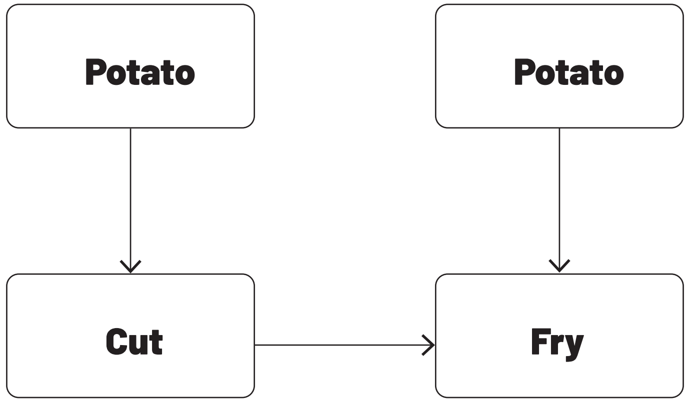
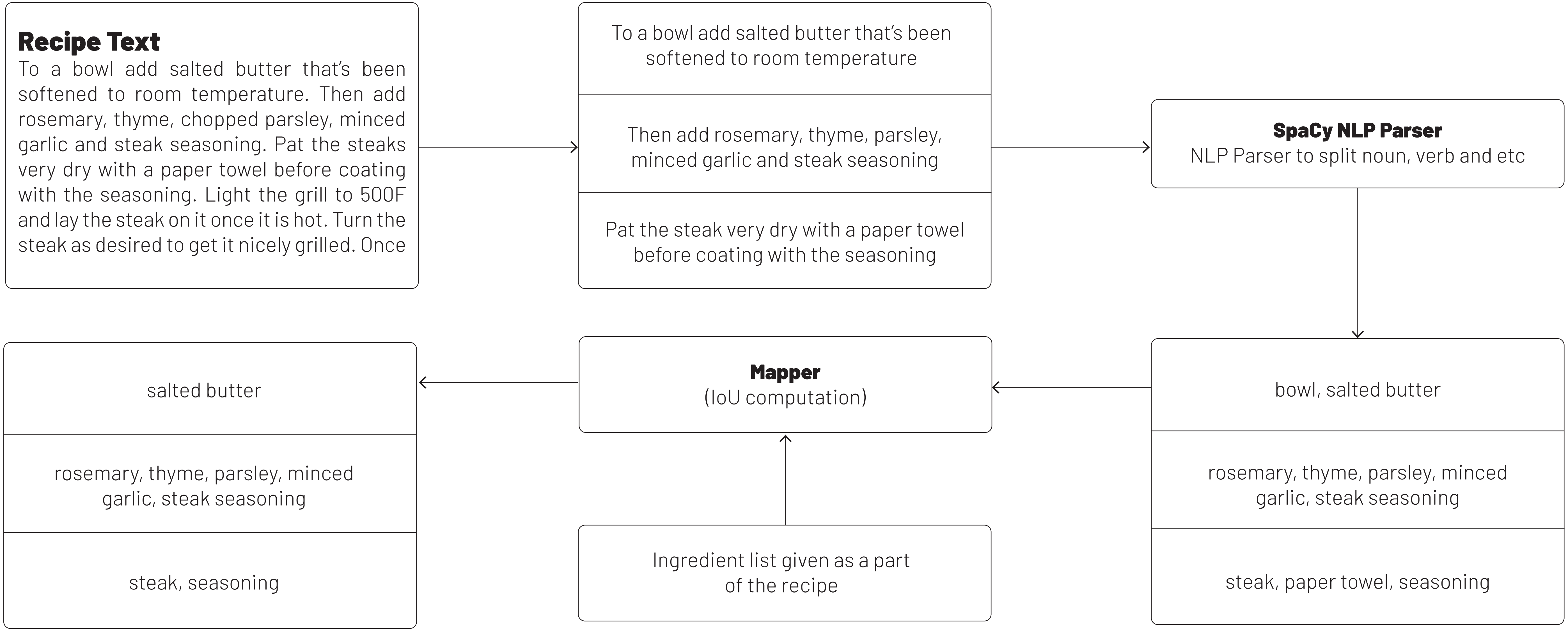


RQ1

Can the process entities be extracted from unstructured data with limited ground truth data?

Extracting Ingredients



Revathy Venkataramanan, Swati Padhee, Saini Rohan Rao, Ronak Kaoshik, Anirudh Sundara Rajan, and Amit Sheth. "Ki-Cook: clustering multimodal cooking representations through knowledge-infused learning." Frontiers in Big Data 6 (2023)

Extracting Cooking Actions

Heat Oven to 350 degrees Fahrenheit	heat, 350 degrees
Place sun-dried tomatoes and boiling water in small bowl	place, boiling
Let stand for 5 minutes or until soft	stand
......	......

Dataset Creation

+ 1000 recipes from Recipe 1M
+ Constituting 10,000 cooking instructions
+ Annotated each cooking instructions with cooking actions

Challenges

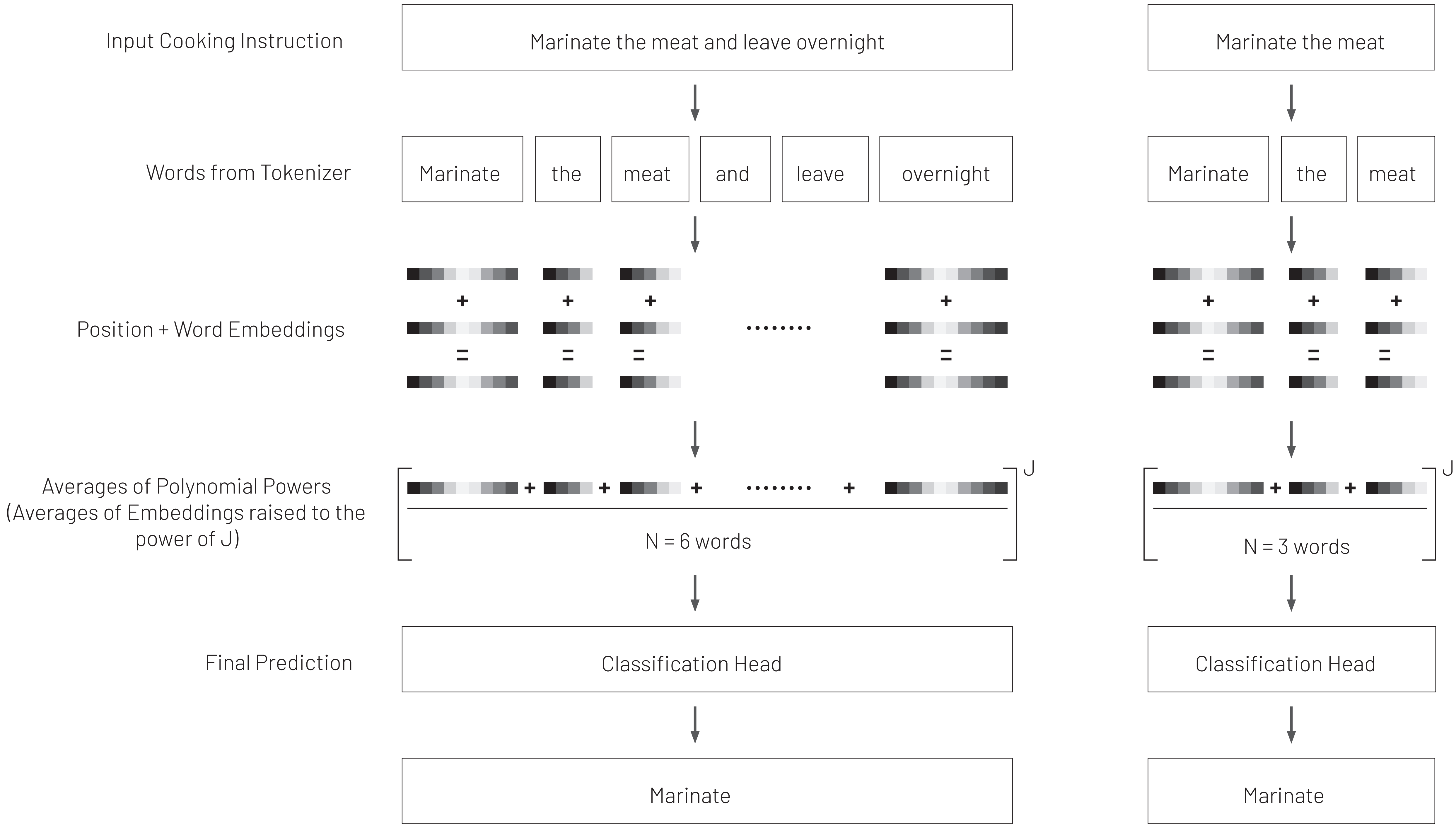
Toss	the	pasta	with	sauce	on	the	pan	on	low-medium	heat

On	low-medium	heat	add	pasta	to	sauce	and	cook	untill	al dente

+ Irregular distribution of words
+ Irregular distribution of cooking words: “boil” is more common than “broil”
+ Written in natural language with Variable length sentences
+ Different sentences conveying the same

CookGen

Proposed Model



Revathy Venkataramanan, Kaushik Roy, Kanak Raj, Renjith Prasad, Yuxin Zi, Vignesh Narayanan, and Amit Sheth. "Cook-Gen: Robust Generative Modeling of Cooking Actions from Recipes." In 2023 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 981-986. IEEE, 2023.

Relationship Extraction

Instruction	Ingredients	Cooking Actions
Mix butter and steak seasoning and marinate steak	butter, steak seasoning, steak	mix, marinate
...	...	...

Prompt

```
In the following cooking instruction, which
cooking action is being performed on which
ingredient?

Instruction: Mix butter and steak seasoning..
Ingredient: butter, steak seasoning, steak
Cooking Action: mix, marinate
```

Large Language Model

Mapping

Mix: [butter, steak seasoning],

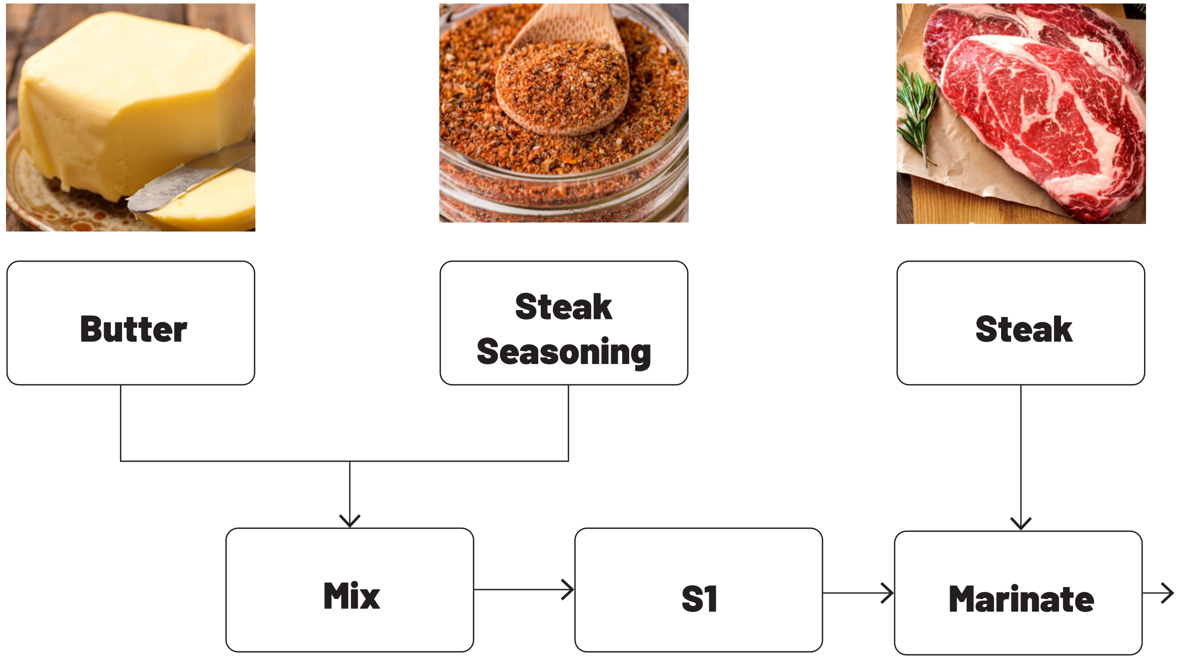
Marinate: [steak]

Ingredient Image Crawler

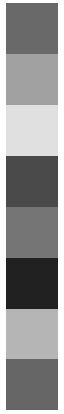
Construction Module

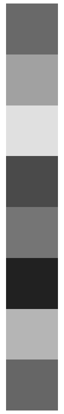
Recipe image

Ingredient images



Recipe Image-to- Recipe Text





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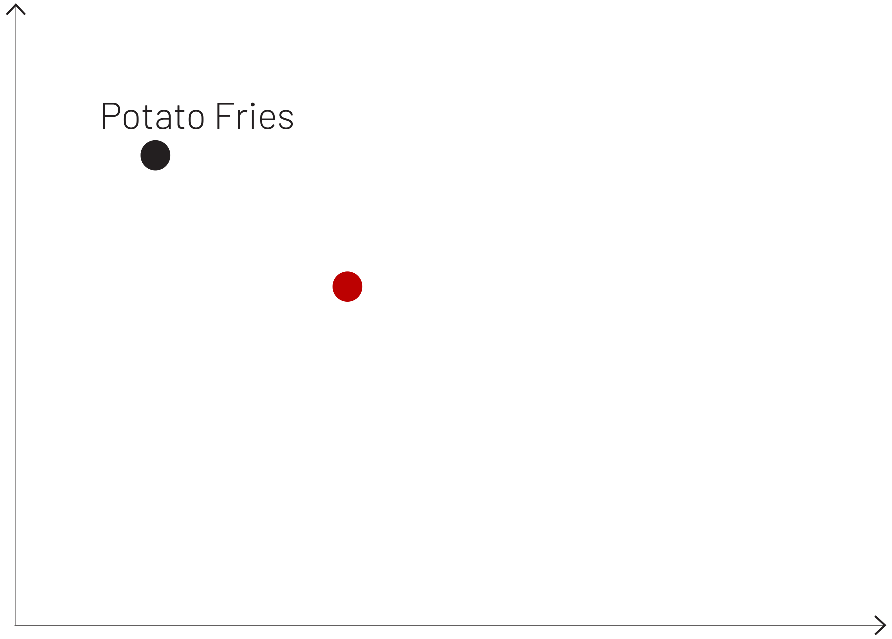

Recipe Image-to- Recipe Text

Cross Modal Retrieval Learning

RecipeText
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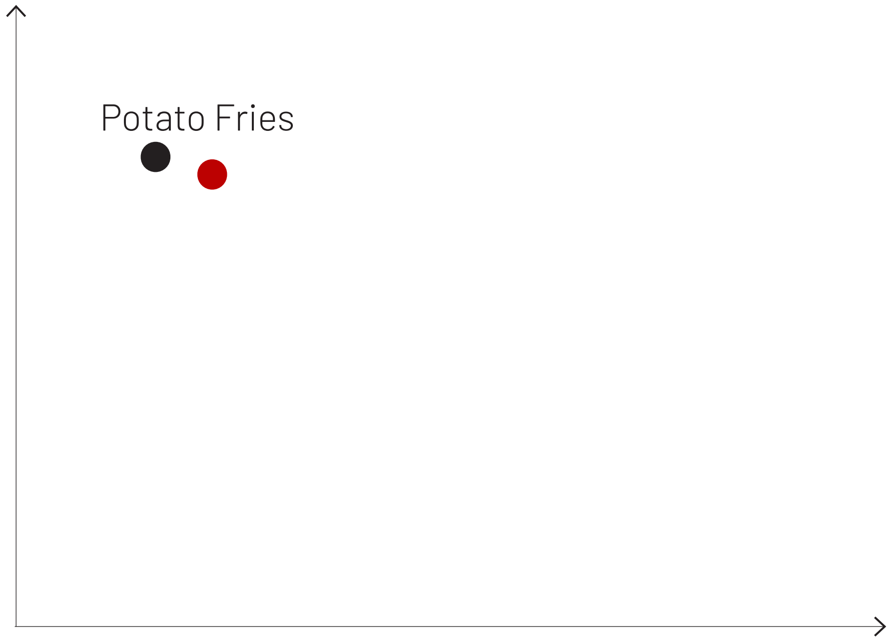
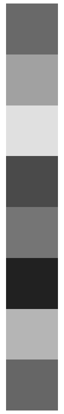


Image Embedding

Text Embedding

Recipe Image-to- Recipe Text

Cross Modal Retrieval Learning



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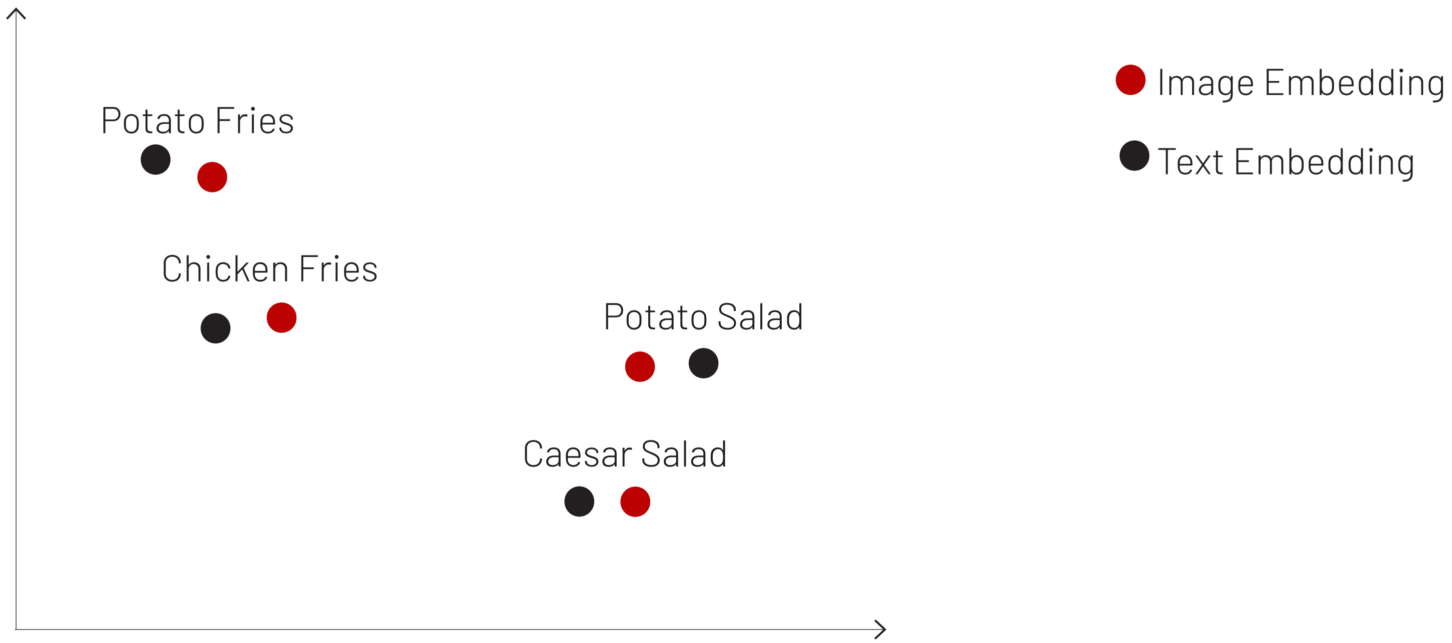

Embedding Space Grouped Based on class names

Recipe Image-to- Recipe Text

Cross Modal Retrieval Learning

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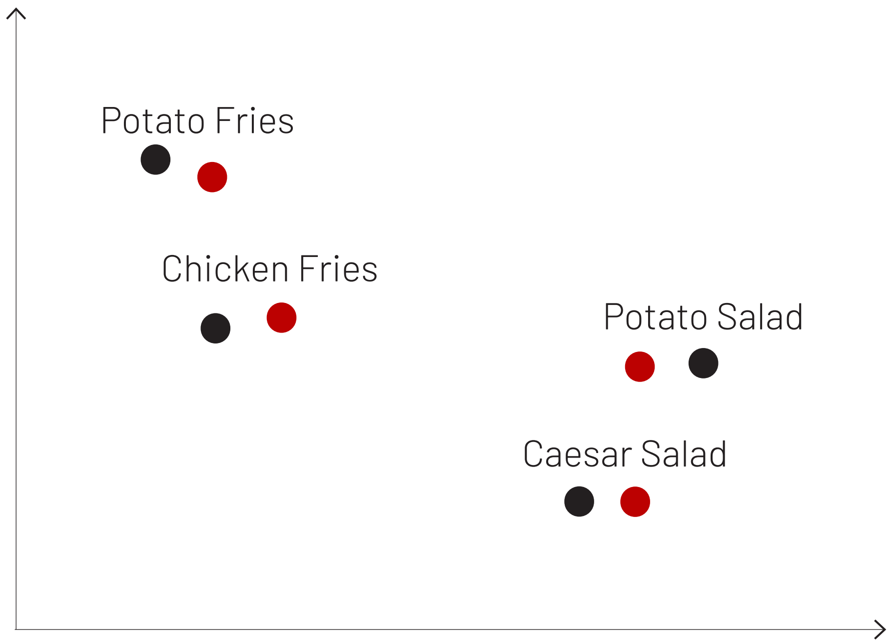
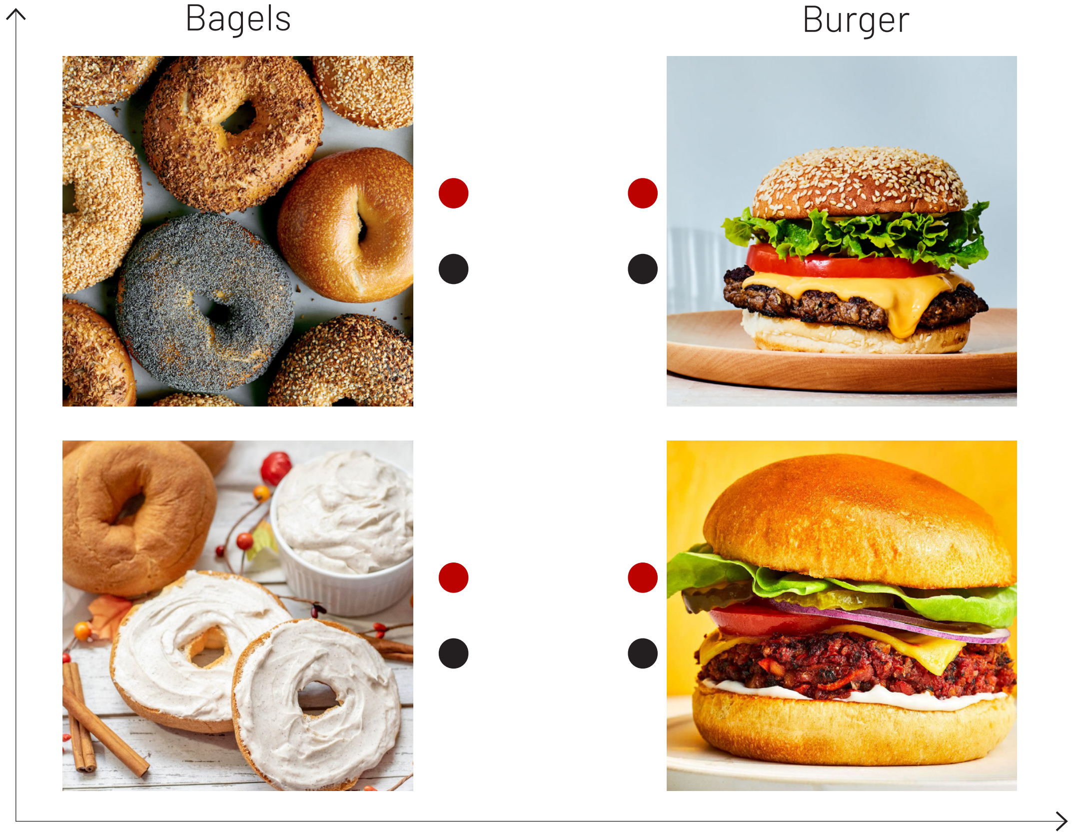


Image Embedding

Text Embedding

Embedding Space Grouped Based on class names



Which cluster should this image go to?

Knowledge-infused Learning

Recipe Similarity Determinant

$$sim(r_i, r_j) = \frac{\sum_{i=1}^{n} w_i \, . \, x}{n} + \frac{\sum_{i=1}^{m} (1 / f_i) \, . \, x}{m}$$

Ki-Cook
Knowledge Infused
Multimodal Clustering

Red Sauce Pasta

Class Name: Pasta

Ingredients

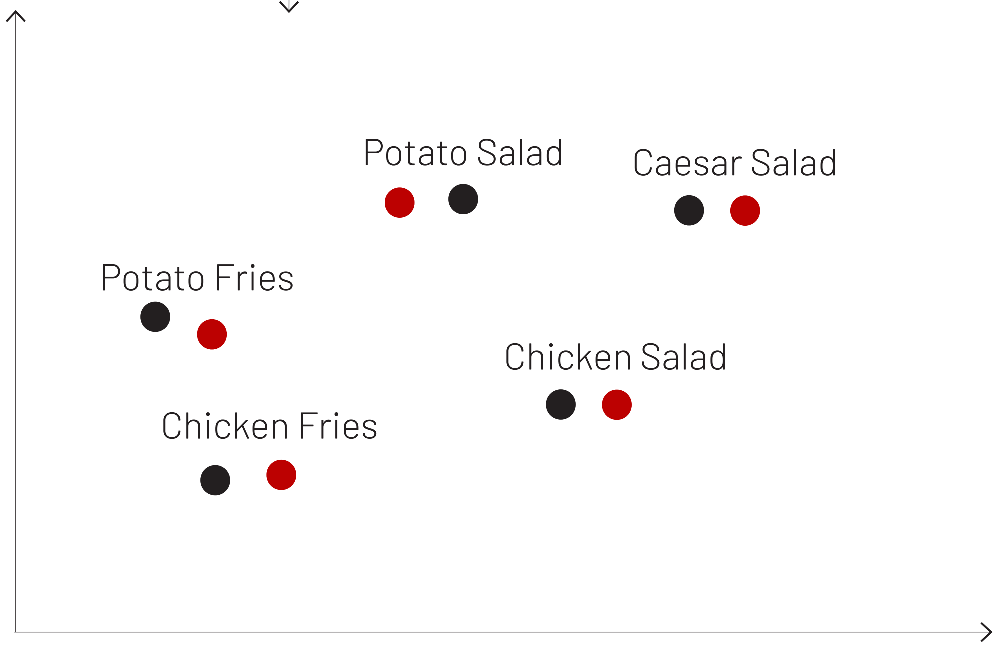
Salt
Pepper
Tomato sauce
Pasta
Olive oil

Green Sauce Pasta

Class Name: Pasta

Ingredients

Salt
Pepper
Basil
Hazelnut
Kale leaves
Pasta
Olive oil



Embedding Space with recipes clustered based on Recipe Similarity Determinant

Revathy Venkataramanan, Swati Padhee, Saini Rohan Rao, Ronak Kaoshik, Anirudh Sundara Rajan, and Amit Sheth. "Ki-Cook: clustering multimodal cooking representations through knowledge-infused learning." Frontiers in Big Data 6 (2023)

Knowledge-Infused Learning Results

Query: Fried Eggplant

Base Model
Recipe: Dilly Cheese Muffins
Ingredient Prediction Accuracy: **0.14**

KiCook Model
Recipe: Low Carb Eggplant Parmesan
Ingredient Prediction Accuracy: **0.28**

Query: Cheddar Chive Biscuits

Base Model
Recipe: Cora's Chocolate Chip Cookies!
Ingredient Prediction Accuracy: **0.44**

KiCook Model
Recipe: Peppery Cheese and Chive Biscuits
Ingredient Prediction Accuracy: **0.44**

Query: Sweet and Sour Chicken Rice

Base Model
Recipe: Peppery Cheese and Chive Biscuits
Ingredient Prediction Accuracy: **0.18**

KiCook Model
Recipe: Chicken Stir fry Oriental
Ingredient Prediction Accuracy: **0.09**

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High level knowledge

Caution | Recommend

Greater than 70
High Glycemic Index | Carb: Fibre >= 10:1
Healthy Carbohydrate

Glycemic index: 78 | Carb: 37g, Fibre: 4g

Potato

Low level data

RQ2

How can process entities be elevated to high-level concepts and represented in a structured format with multimodal data for reasoning?

Types of Knowledge Sources

Knowledge Type	**Source**
Ingredient and its Nutrition	United States Food and Drug Adminstration (USFDA)
Disease specific knowledge	MayoClinic and National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK)
Cooking Taxonomy	Wikidata
Carcinogens	Published Papers
Smoke Point	Kendall Regan Research Center, University of Colorado
Glycemic Index and Glycemic Load	Glycemic Index Research, University of Sydney
Nutrition Retention	United States Food and Drug Administration

Diabetes Medical Guidelines

MayoClinic

Recommend

Healthy Carbohydrates

Fiber-rich food

Whole grains

Heart Healthy Items

Good Fats

Protein

Low fat, non fat

Avoid

Saturated fats

Trans fats

Cholesterol

Sodium

Added Sugar

Refined carbohydrates

Ultra processed

Deep fried

Whole grain

If carbohydrate:fibre is 10:1 or greater for a grain, then it is a whole-grain food

Fiber rich

If carbohydrate:fibre is 10:1 or greater, then food is fiber rich

Heart Healthy Items

If polyunsaturated fat or monounsaturated fat or omega-3 is present, then heart healthy item

Low fat non fat

high: more than 17.5g; medium: 3 to 17.5g; low: less than 3g, fat-free: less than 0.5g. All per 100gram

Saturated Fat

10% of calories from saturated fat is allowed. 1g fat = 9kcal

Trans Fat

2.2 gram per day in 2000 kcal or 0.9% of calories from trans fat allowed

Cholesterol

200 milligram per day or 15milligram per 100kcal

Sodium

2300mg per day or \textless{}1.1 mg/kcal = 2,300 mg at 2,100 kcal is allowed

Refined Carbohydrate

If 10g carbohydrate:≥1g dietary fiber & ≤2g free sugars per 1g dietary fiber, then good carbohydrate.
Else, refined carbohydrate

USFDA Database

Name

Category

Nutrition Content

Food density

Diabetes Reasoning Knowledge Graph

Ingredient

Nutrition: {iron: 0.788mg, cholesterol: 71.2mg, calcium: 5.86mg,..}

Name: Pork, ground, raw

USFDA Category: Pork Products

Source URL: https://fdc.nal.usda.gov/fdc-app.html#/food-details/2514745

FoodGroup

KnowledgeSource: MayoClinic

Description: Individuals with risk of heart disease such as diabetes must limit cholesterol intake . . .

SampleIngredients: [butter, heavy cream, bacon...]

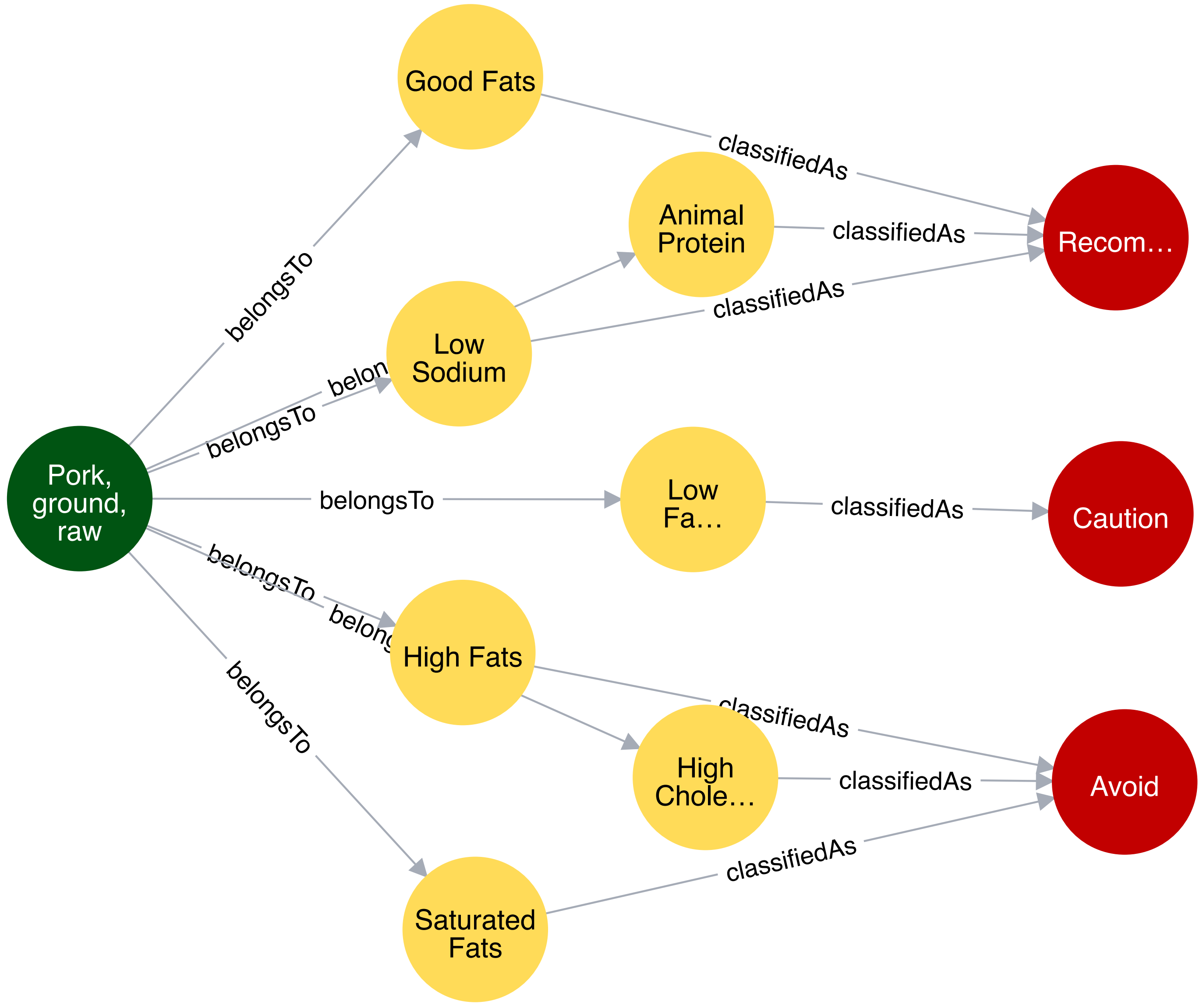
belongsTo

Allowed: 200mg/day or 15mg / kCal

Present: 30.56 mg/kCal

Explanation: This food item has 71.2 milligrams of cholesterol in 233 kcal of calories...UCSF suggests no more than 200 milligrams per day if there is a risk of heart disease (https://www.ucsfhealth.org/education/cholesterol-content-of-foods). CDC shows clear evidence of diabetes patients at the risk of heart disease (https://www.cdc.gov/diabetes/diabetes-complications/diabetes-and-your-heart.html)

Tag: High Cholesterol



Sources: MayoClinic, NIDDK, CDC, Harvard Medical School, UCSF Health,...

Cooking Taxonomy

Taxonomy

The cooking methods were classified into categories such as

+ heat (boil)

+ mechanical (peel)

+ chemical (pickling)

Heat-based methods were further broken down into subcategories such as

+ dry heat (baking)

+ liquid-based (boiling)

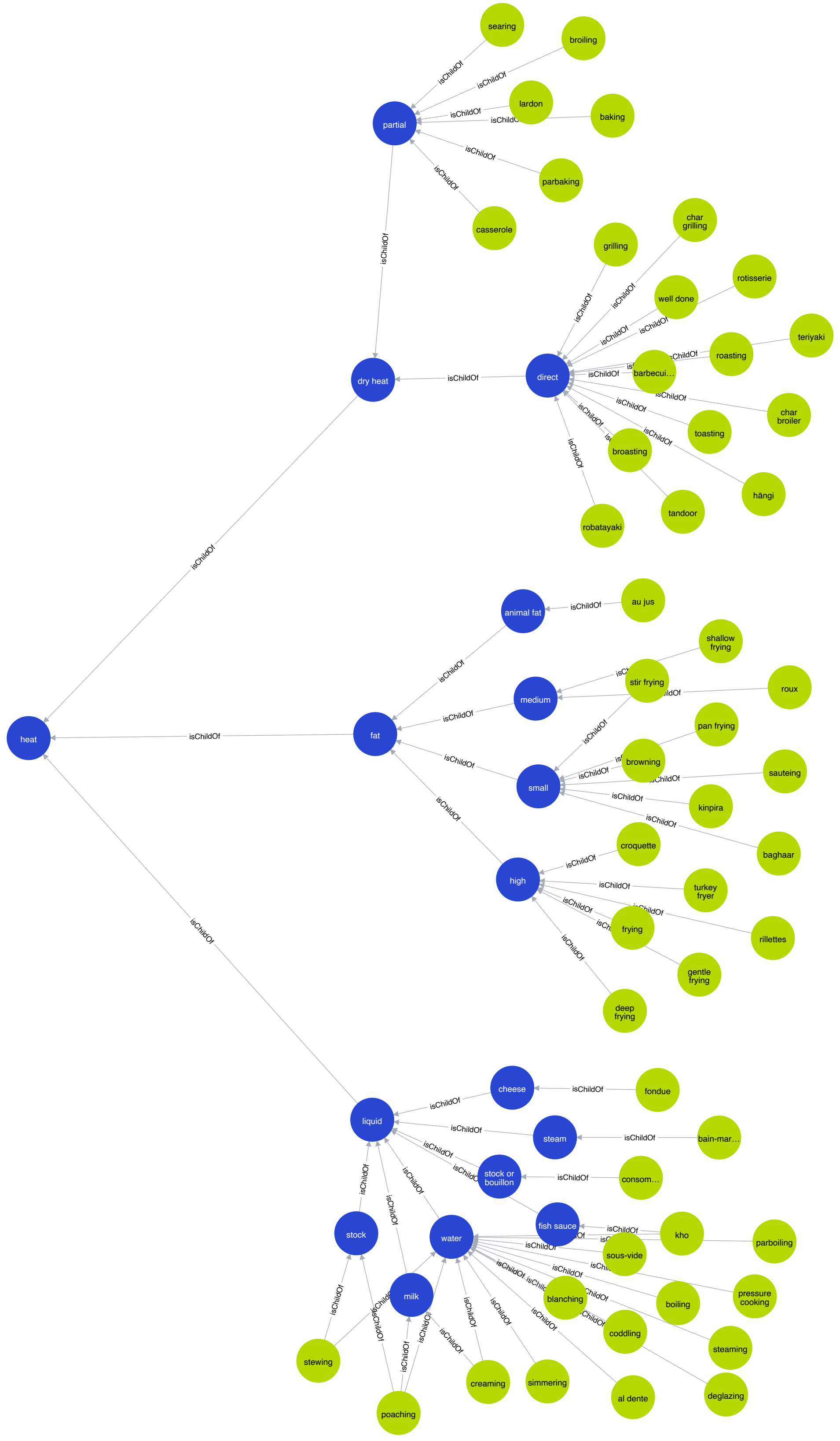
+ fat-based (deep fry)

CookingMethod

Name: Shallow Frying

Description: Shallow frying is a hot oil based cooking technique. It is typically used to prepare portion sized cuts of meat, fish potatoes and patties such as fritters

Source URL: http://dbpedia.org/resource/Shallow_Frying



Source: Wikidata, DBPedia

Carcinogen Causal Knowledge Graph

Health Risks

Carcinogenic compounds are linked to an increased risk of cancer and other chronic health issues.

+ HeteroCyclic Amines (HCA)
+ Polycyclic Aromatic Hydrocarbons (PAH)
+ Advanced Glycation End products (AGE)

Carcinogen

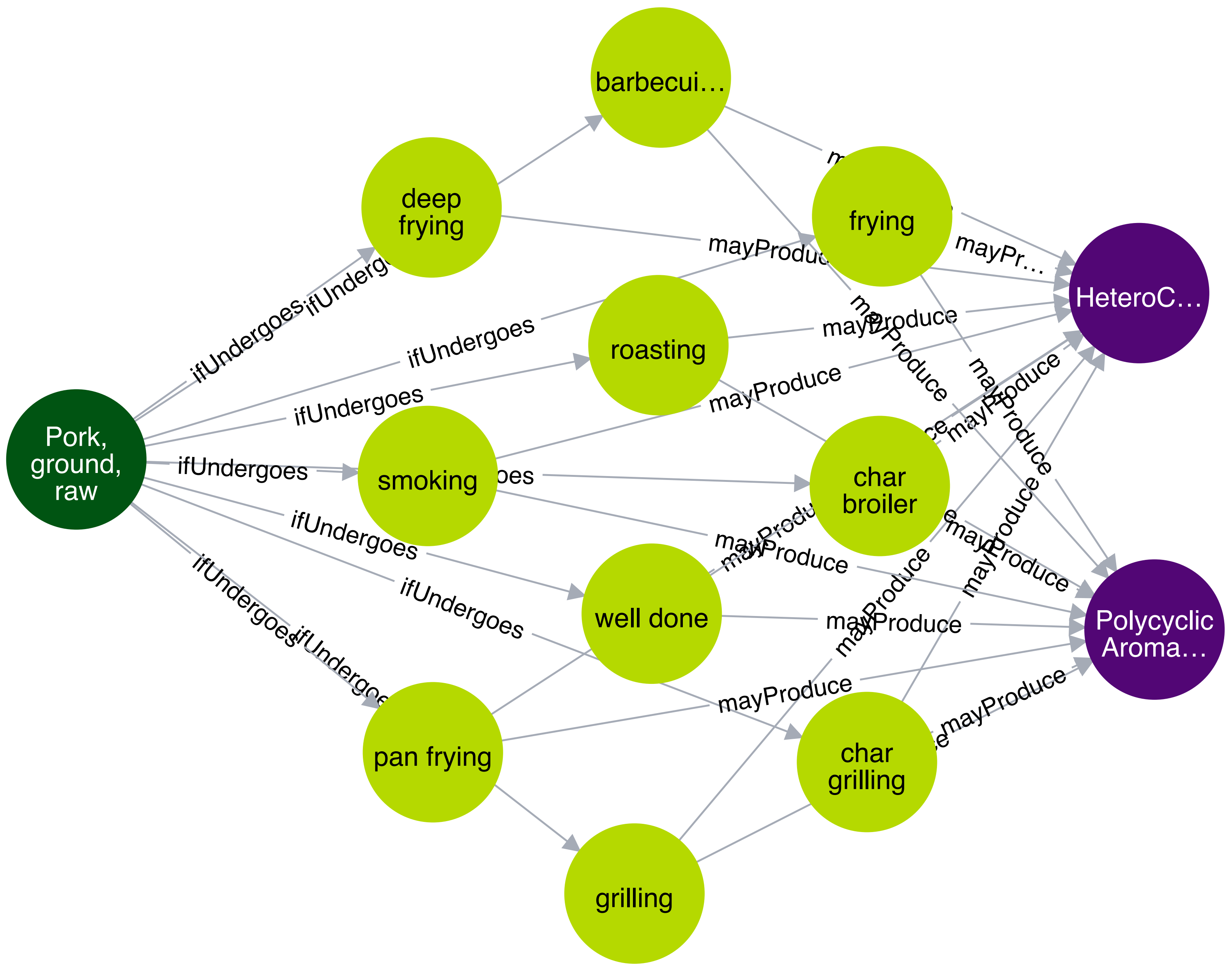
Name: HeteroCyclic Amines (HCA)

Reason: HeteroCyclic Amines (HCA) form when amino acids and creatine react at high cooking temperatures and are formed in greater quantities when meats are overcooked or blackened. Cooking for a long period of time also results in such toxic components. To add, deep frying also introduces HCA - https://pmc.ncbi.nlm.nih.gov/articles/PMC3756514/

Cooking Methods: grilling, smoking, roasting, barbecuing, char grilled,...

Ingredients: chicken steak, red meat, fish, muscle meat, . .

Source URL: https://www.precisionnutrition.com/all-about-cooking-carcinogens, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2850217/



Sources: Healthline, Published papers

Smoke Point Knowledge

Health Risks

Heating fats beyond smoking points produce free radicals that can worsen inflammation

hasSmokePoint

Name: Walnut Oil

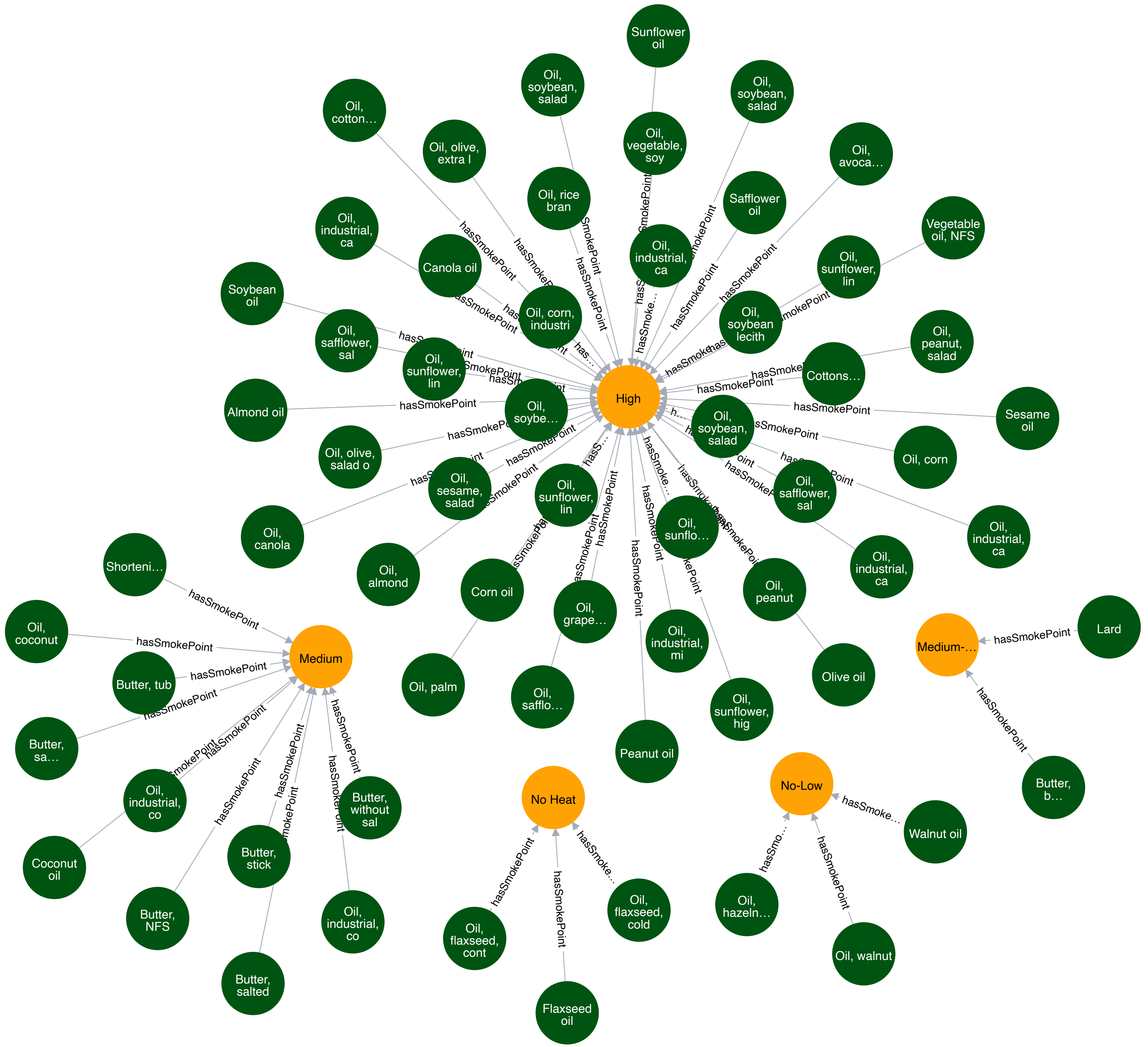
Additional Information: Though these oils have higher smoke points, they are delicate and can become bitter when heated too much. They are recommended to be used as finishing oils to maintain their flavor and aroma.

Reason: Heating oils and fats beyond their smoking point may release free radicals (toxic compounds). Source: https://www.chhs.colostate.edu/krnc/monthly-blog/cooking-with-fats-and-oils/

Category: No heat - Low heat

Smoke Point: 430 F

Source URL: https://www.chhs.colostate.edu/krnc/monthly-blog/cooking-with-fats-and-oils/



Sources: Kendall Reagan Nutrition Center, Colorado State University; Wikidata

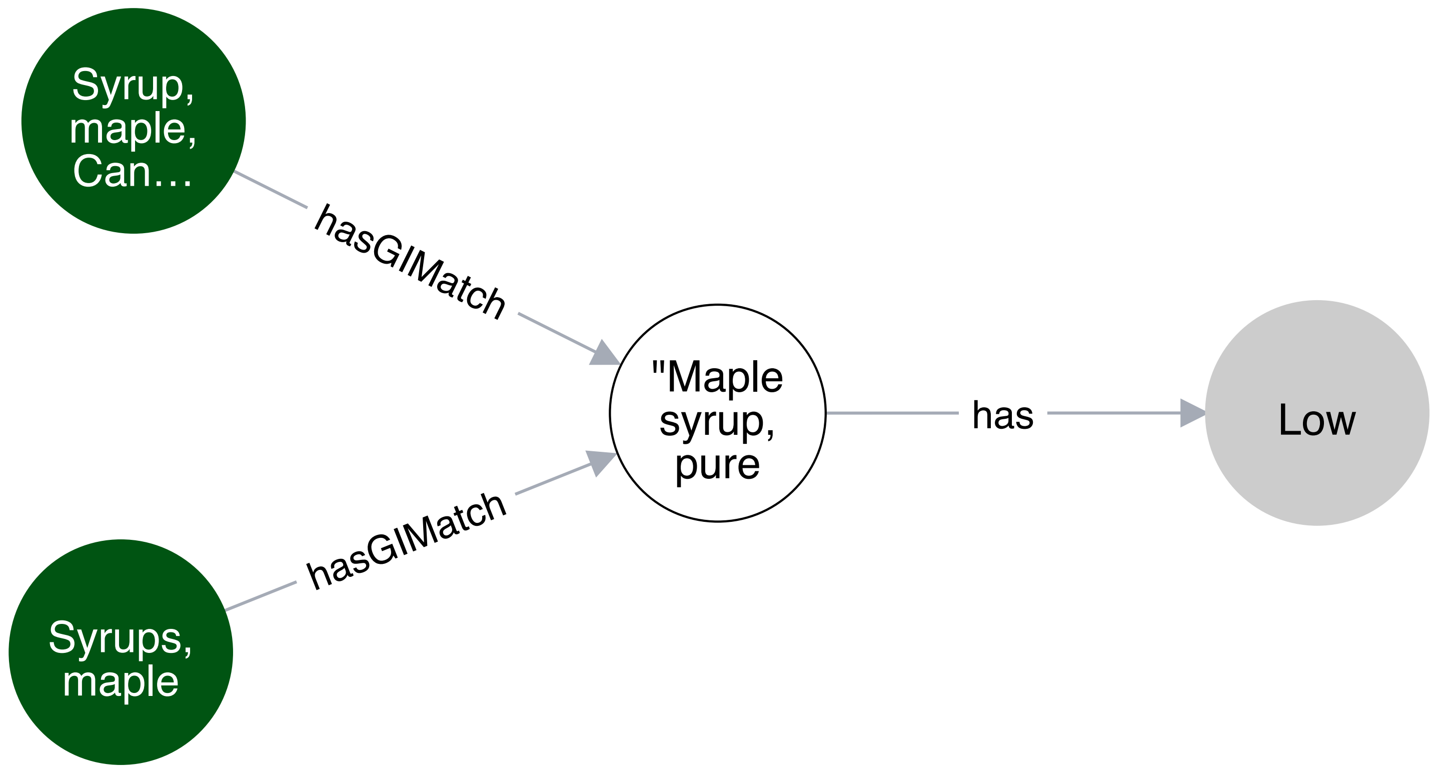
Glycemic Index Knowledge

Glycemic Index (GI)

measures how quickly carbohydrate-containing foods raise blood glucose levels.

High-GI foods: Not Good, consumed in moderation

Low-GI foods : Recommended



hasGIMatch

GI: 54

cosine sim: 1.0

GIIngredient

Name: Maple syrup, pure Canadian

Manufacturer: Queen Foods, Australia

GI: 54

GL: 3.0

Category: Low

SourceURL: https://glycemicindex.com/

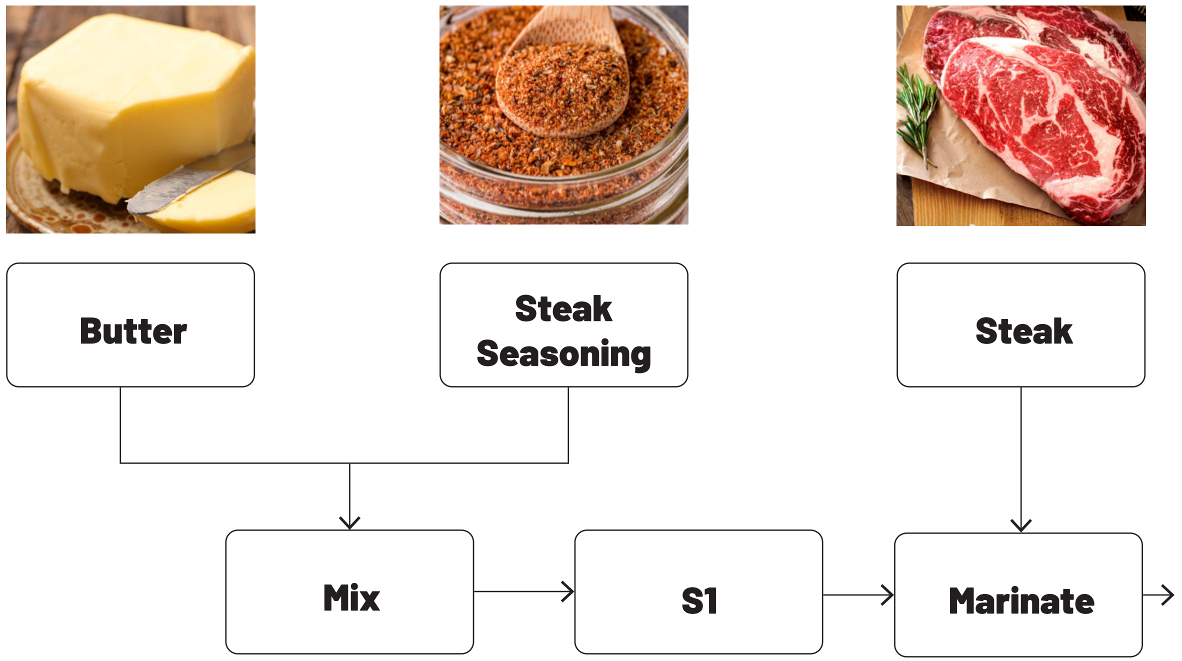
SourceName: University of Sydney, Glycemic Index Resrch and GI News

Sources

+ Sydney University Glycemic Index Research Service

Knowledge Graph Overview

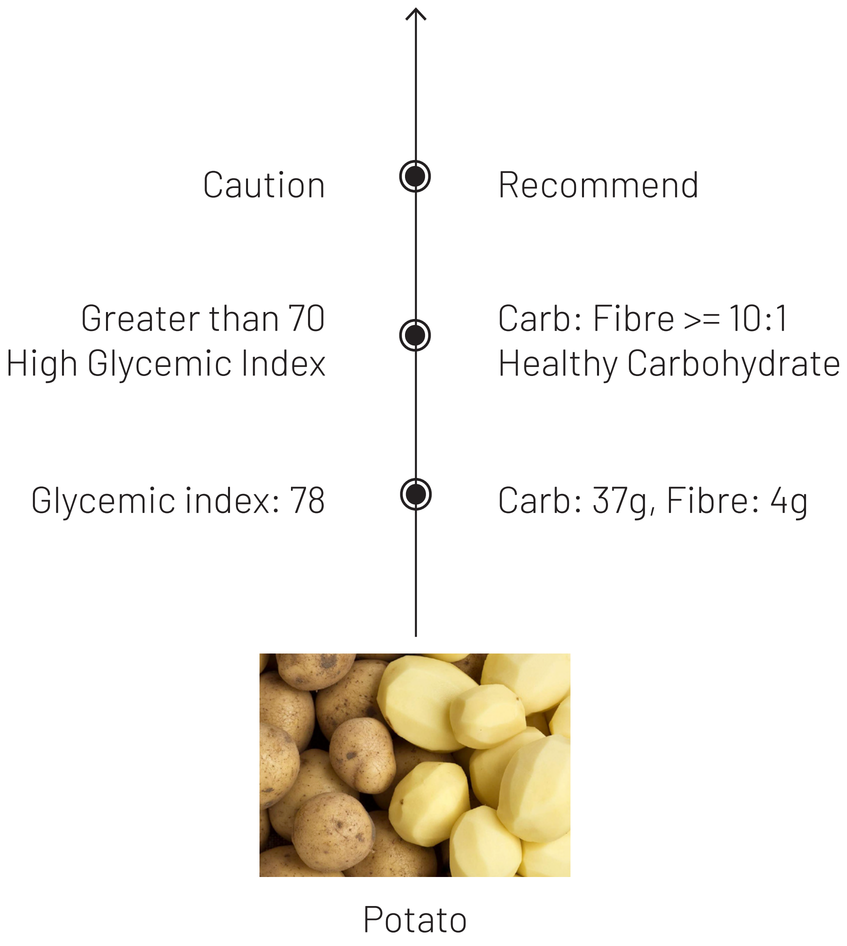
Components	**Quantity**
# Nodes (LPG)	17,598
# Relationships (LPG)	677,522
# Triples (RDF)	1,294,439
# Node Types	9
# Relationship Types	8
# Ingredients	13, 538
# Cooking Methods	154
# Ingredient —> FoodGroup —> DiabetesLabel	115,278
# Ingreidnet —> CookingMethod —> Carcinogen	71, 440
# Ingredient —> SmokePoint	65
# Ingredient —> GlycemicIndex	59,124



Knowledge Types

+ Ingredient and Nutrition
+ Disease specific knowledge
+ Cooking Taxonomy
+ Carcinogen Formation
+ Smoke Point
+ Glycemic Index
+ Nutrition Retention

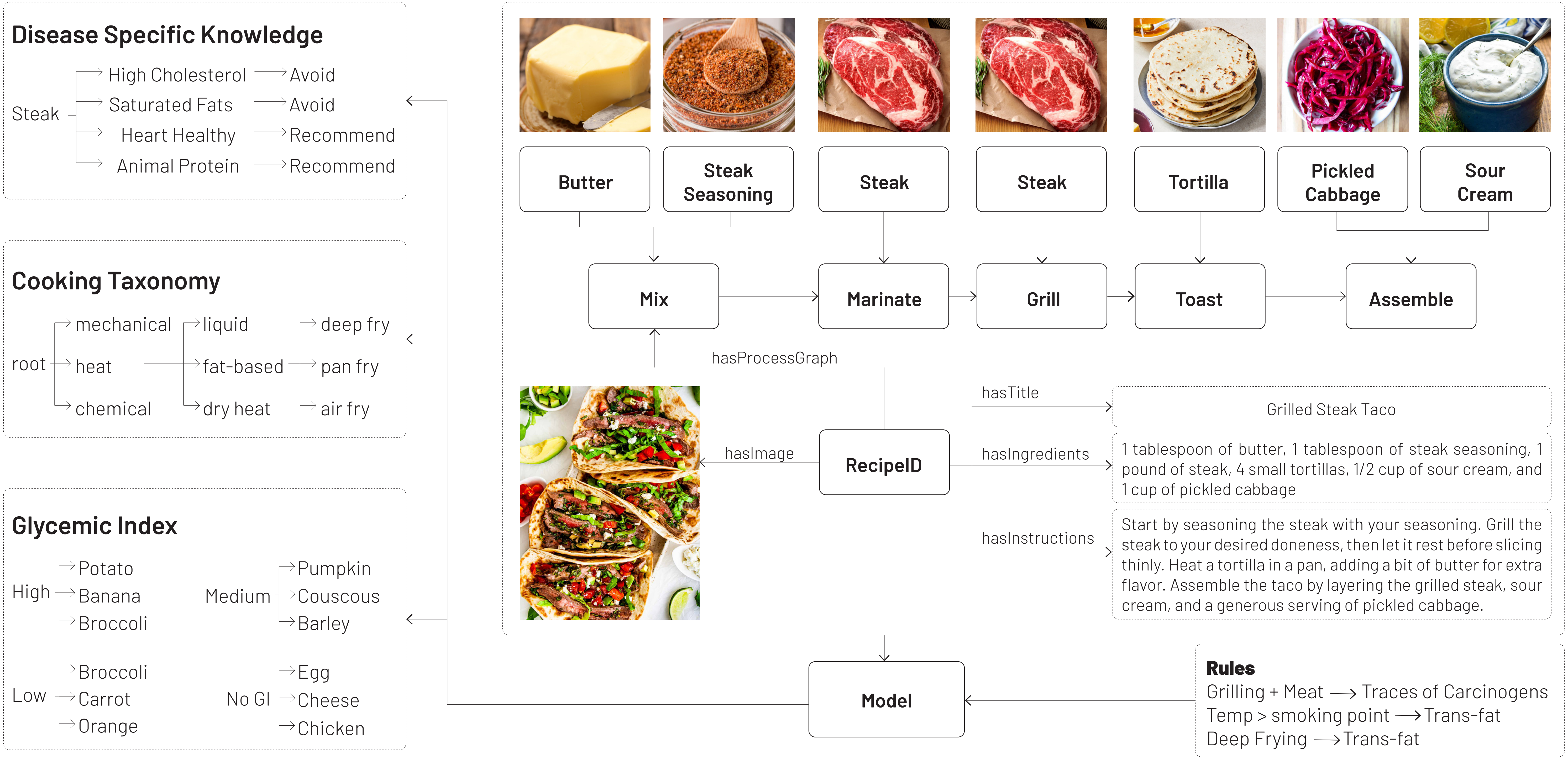
High level knowledge



Low level data

Extracted Entities, Multimodal Data, Multicontextual Knowledge - How can we represent them?

Dynamic Multimodal Process Knowledge Graph for Recipes



Revathy Venkataramanan, Chathurangi Shyalika and Amit Sheth. "Dynamic Multimodal Process Knowledge Graphs: A Neurosymbolic Framework for Compositional Reasoning" in IEEE Internet Computing 29, no. 1(2025): 86-92.

Features: Dynamic Multimodal Process Knowledge Graph

Make Fried Steak Taco suitable for diabetes and vegetarians

Steak is an animal product, incompatible for vegetarians (USFDA + Rules)

Sour cream has high fat, not much suitable diabetes (Diabetes KG)

Deep frying introduces trans-fat (Rules)

Modifications

Replace steak with cauliflower, compatible for vegetarians (USFDA + GI + Ing Sub)

Replace sour cream with yogurt, as it is less fat and low GI (Diabetes KG + GI + Ing Sub)

Replace deep frying with air frying. Not boiling, which is healthy but water based cooking method. (Cooking taxonomy)

Neurosymbolic Queries

Give me recipes with this ingredient

Give me recipes with no cholesterol
(Look into ingredients + Diabetes reasoning graph)

Is this recipe good for diabetes?

Representation learning, Explainability, Traceability, Abstraction and Causal reasoning

RecipeText
Peel potatoes, then cut them into thin strips. Heat oil in a deep fryer or skillet. Then fry the potatoes in batches until golden brown...

Explainable Recommendation

Can I eat this food? Caution

Explanations
Potato - Healthy CHO, High GI [WebMd]
Canola Oil - unrefined, good fat [WebMD]
Deep frying - Trans Fat [USFDA]
Potato + frying - Vitamin A&C loss [USFDA]
Allergens - dairy free, nut free

RQ3

How can explainable recommendation results be produced that are supported by reasoning and can be traced back to trusted sources?

Dataset

Suitable for Diabetes

Sources

+ Mayo Clinic
+ Diabetes UK
+ Diabetes Hub

Method

+ Curated recipes designed specifically for diabetes management.
+ Sourced from trusted medical websites that focus on dietary guidelines for diabetes patients.
+ Ensures the dataset is based on reputable, evidence-based sources to ensure reliability.

Data Points

+ 3,807 diabetes-specific recipes collected and utilized for analysis.

Not Suitable for Diabetes

Sources

+ Mayo Clinic
+ Recipe1M Dataset

Method

+ Identified potentially unsuitable recipes using keywords from Mayo Clinic's dietary guidelines for diabetes patients.
+ Keywords included terms like 'ribs', 'pork bacon', 'sausage', 'cookies', 'pancakes', etc.
+ Conducted keyword searches in recipe titles and ingredients from the Recipe1M dataset to find recipes that might be unsuitable for diabetes management.
+ Randomly selected 3,800 recipes to maintain class balance in the dataset.

Data Points

+ 3,800 non-diabetes-specific recipes were randomly selected

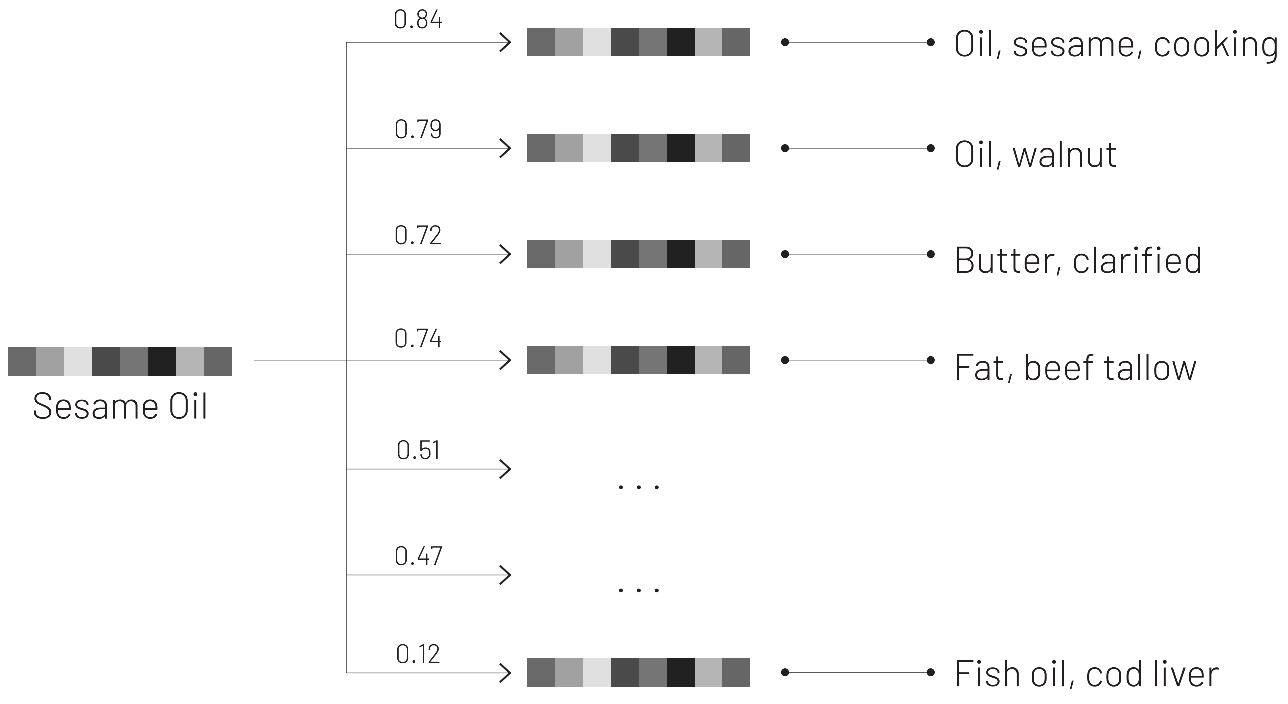
Recipe to Knowledge Paths

Recipe Ingredient: Sesame Oil

Database Ingredient: Oil, sesame, salad or cooking

$$\mathrm{sim}(ing_i, ing_j) = \frac{\mathrm{cos\_sim}(e_i, e_j) + J(t(ing_i), t(ing_j))}{n}$$

J - Jaccard similarity
t- tokens
cos_sim - Cosine Similarity
e - embedding generated by a model
ing_i - query ing
ing_j - ingredient from USFDA database

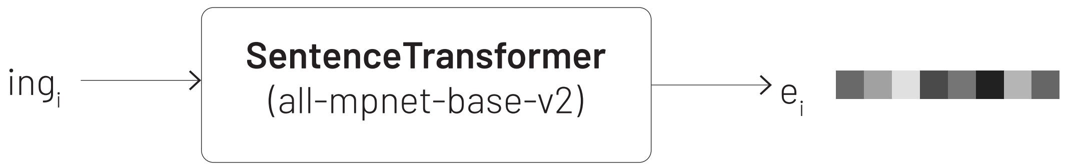


Rank the similarity and identify the most similar ingredient from USFDA database

Neural

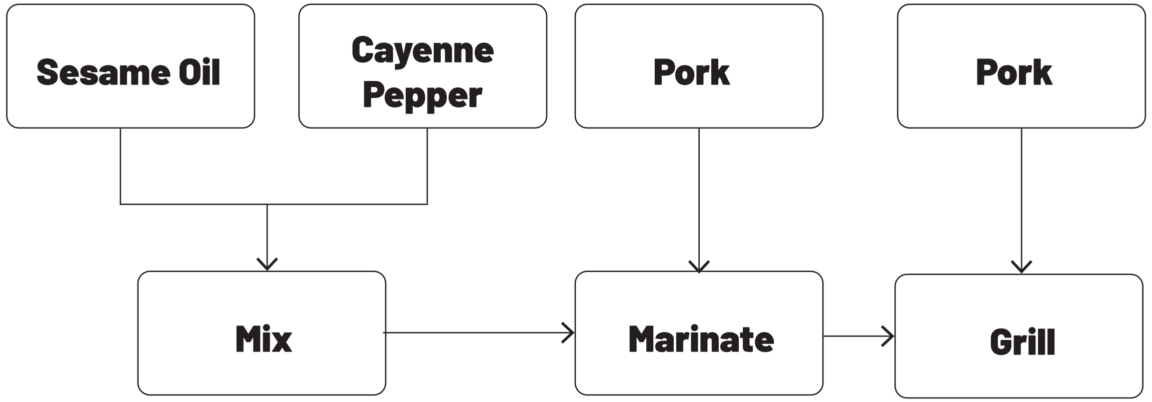
Embeddings are effective at capturing synonyms and identifying words with similar meanings due to their pattern mining abilities

Example: Cilantro vs Coriander, Garbanzo beans vs Chickpeas



Grilled Asian Spiced Pork Ribs

Ingredients in Recipe	Ingredients in USFDA		
Pork	Pork, ribs	High Cholesterol	Avoid
		Saturated Fats	Avoid
		Heart Healthy	Recommend
		Animal Protein	Recommend
Soy Sauce	Soy sauce	High Sodium	Avoid
		Low Saturated Fat	Caution
		Low fat, Non fat	Recommend
		Healthy Carbohydrate	Recommend
Sesame oil	Oil, sesame, salad or cooking	Heart Healthy	Recommend
		Good Fat	Recommend
		High Fat	Avoid
		Saturated Fat	Avoid
Cayenne pepper	Spices, red cayenne	Low Sodium	Recommend
		Healthy Carbohydrate	Recommend
Gathered through recipe process knowledge graph	Pork + Grill	Carcinogens (PAH)	Avoid
		Carcinogens (HCA)	Avoid
	Sesame Oil + Grill	Under Smoke Point	Recommend



Individual Inferencing

Grilled Asian Spiced Pork Ribs

Pork	High Cholesterol	Avoid
	Saturated Fats	Avoid
	Heart Healthy	Recommend
	Animal Protein	Recommend
Soy sauce	High Sodium	Avoid
	Low Saturated Fat	Caution
	Low fat, Non fat	Recommend
	Healthy Carbohydrate	Recommend
Sesame Oil	Heart Healthy	Recommend
	Good Fat	Recommend
	High Fat	Avoid
	Saturated Fat	Avoid
Spices, red cayenne	Low Sodium	Recommend
	Healthy Carbohydrate	Recommend
Pork + Grill	Carcinogens (PAH)	Avoid
	Carcinogens (HCA)	Avoid
Sesame Oil + Grill	Under Smoke Point	Recommend

?

Individual Inferencing

Grilled Asian Spiced Pork Ribs

Pork
- → High Cholesterol → Avoid
- → Saturated Fats → Avoid
- → Heart Healthy → Recommend
- → Animal Protein → Recommend

Soy sauce
- → High Sodium → Avoid
- → Low Saturated Fat → Caution
- → Low fat, Non fat → Recommend
- → Healthy Carbohydrate → Recommend

Sesame Oil
- → Heart Healthy → Recommend
- → Good Fat → Recommend
- → High Fat → Avoid
- → Saturated Fat → Avoid

Spices, red cayenne
- → Low Sodium → Recommend
- → Healthy Carbohydrate → Recommend

Pork + Grill
- → Carcinogens (PAH) → Avoid
- → Carcinogens (HCA) → Avoid

Sesame Oil + Grill
- → Under Smoke Point → Recommend

?

Compositional Reasoning

Knowledge Graph based Bayesian Inferencing

Symbolic

Given these knowledge paths for a recipe, what is the probability that the recipe i suitable or not suitable

$$P(S \mid K_R) = \frac{P(K_R \mid S)\,P(S)}{P(K_R)}$$

$$P(\sim S \mid K_R) = \frac{P(K_R \mid \sim S)\,P(\sim S)}{P(K_R)}$$

$$P(S \mid K_R) = \frac{P(K_R \mid S)\,P(S)}{P(K_R)}$$

Posterior probability that the recipe is suitable given the observed ingredient paths

Prior probabilities of a recipe being suitable and not suitable

Likelihood of observing the set of paths K_R in recipes that are labeled as suitable.

Evidence, the observed data, which normalizes the posterior probability

Comparative Results of KG-based Bayesian

	Equal weight of Ingredients			Relative weight of Ingredients		
	Accuracy	Precision	Recall	Accuracy	Precision	Recall
Random	0.4832	0.4845	0.4819	0.4832	0.4845	0.4819
Proportional	0.4588	0.4616	0.4782	0.4327	0.4413	0.4512
Normalized weights	0.6109	0.594	0.7072	0.5006	0.503	0.3258
Inverse Freq.	0.504	0.5027	0.997	0.4865	0.4937	0.9591
LR Weights	0.5101	0.5058	0.992	0.4515	0.4723	0.8041
Self-Attention Weights	0.7855	0.7233	0.9265	0.595	0.599	0.58
Neural Network	0.8908	1.0	0.8908	0.9021	1.0	0.9021
KG-Bayesian	**0.9478**	**0.9405**	**0.9607**	**0.9439**	**0.9411**	**0.9518**

Findings

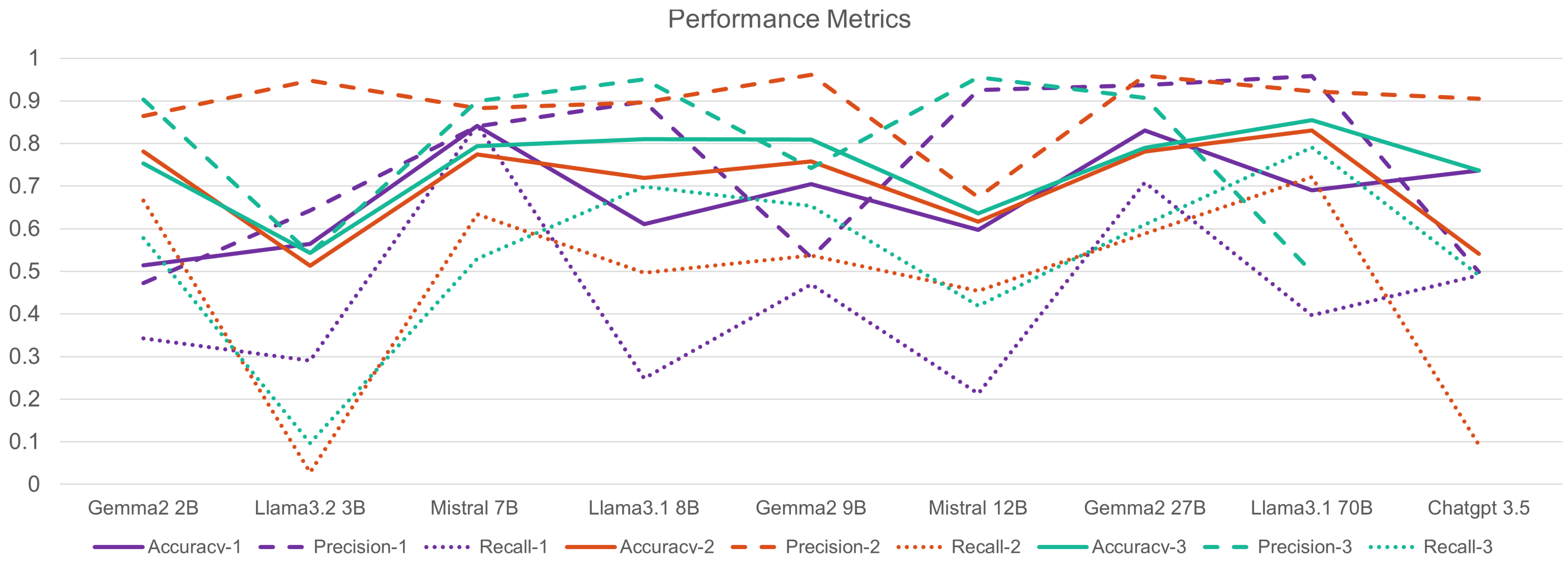
+ Decisions based on simple proportional count of recommend, avoid and caution proved to be insufficient

+ Bayesian also does not require large scale data or retraining

+ Including relative weights brought accuracy down due to data inaccuracies happened during extraction.

Eg: 2/3 of cup —> 23 cup

Comparison with LLMs



Findings

+ Inclination to one class - not suitable - being safe

+ Retrieving knowledge from vast embedding space

+ Connecting relevant information to form inferences

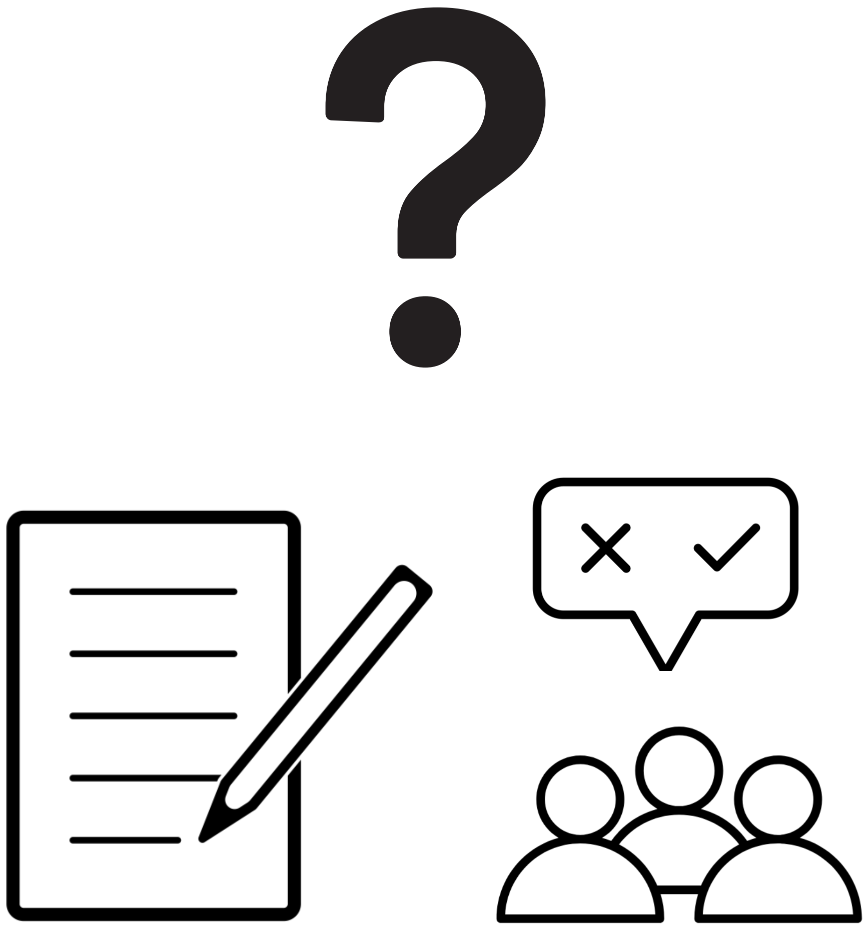
+ Conflicting internal and external knowledge

+ Not always cited to a source

+ Bias towards one set of reasons

Good Fat, Saturated Fat, Fiber-rich - most

High dairy fat, Non fat, Low fat - least



RQ4

Do the users accept the explanations given by the system interms of clarity, relevance, trustworthiness and format?

User Evaluation Study

Hypothesis 1
Does the user perceive the explanation as sufficiently clear to determine the relevance of the recommendation?

Hypothesis 2
Does the user find the explanation provided by the system to be trustworthy?

Number of Participants - 46
Number of Recipes - 3
Method of Evaluation - Survey, 4 questions/Recipe
Type of answers - 5 point Likert scale

Explanations that can be traced back to trusted sources

Recipe Suitability for Diabetes: Not Suitable

Explanations

6 lbs Pork Ribs

Pork, ribs —> High Cholesterol —> Avoid,
Pork, ribs —> Saturated Fats —> Avoid,
Pork, ribs —> Low Fiber —> Caution,
Pork, ribs —> Heart Healthy Items —> Recommend,
Pork, ribs —> Animal Protein —> Recommend,

Relative weight of ingredient in the recipe - 58.95%
Ingredient Decision - Suitable Probability: 1.454 e-27 (~0.0); Not Suitable Probability: 1.0
. . . .

2 tablespoons Sesame oil

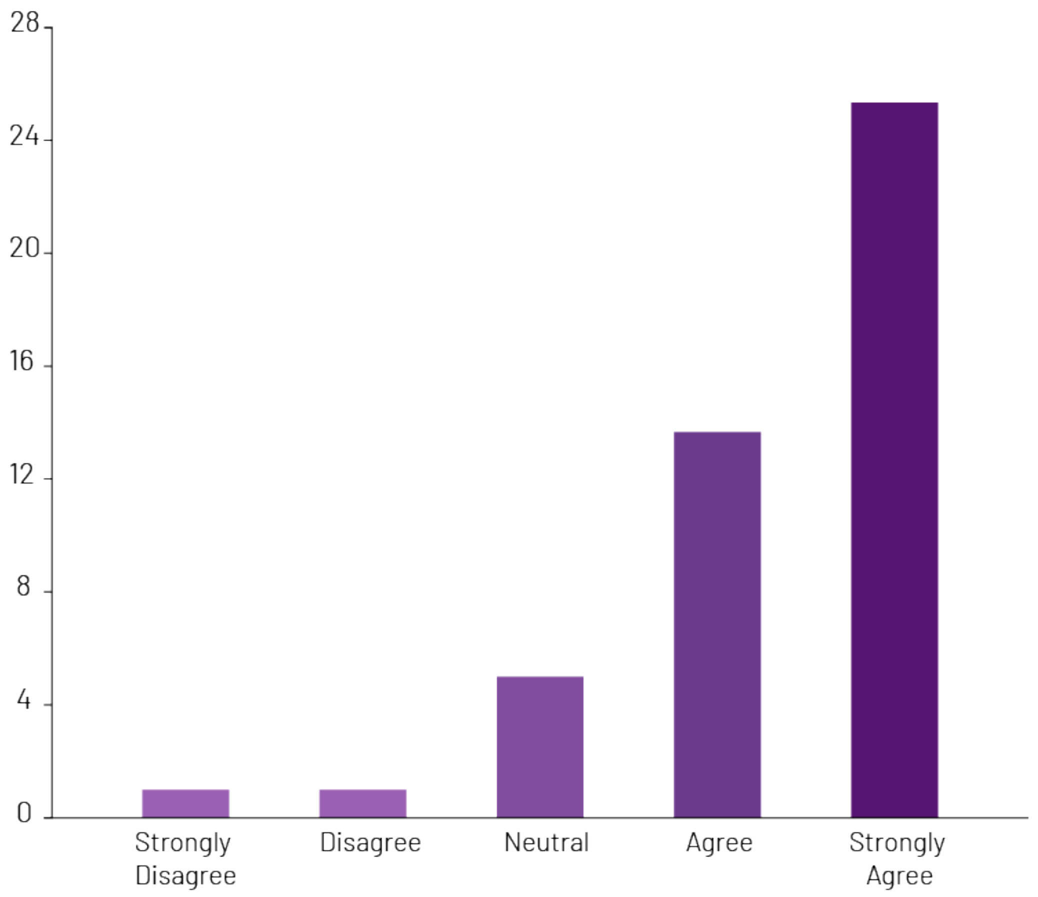
Sesame oil —> Heart Healthy Items —> Recommend,
Sesame oil —> Good Fats —> Recommend,
Sesame oil —> Saturated Fats —> Avoid

Relative weight of ingredient in the recipe - 2.03%
Ingredient Decision - Suitable Probability: 1.0; Not Suitable Probability : 1.016 e-06 (~0.0)

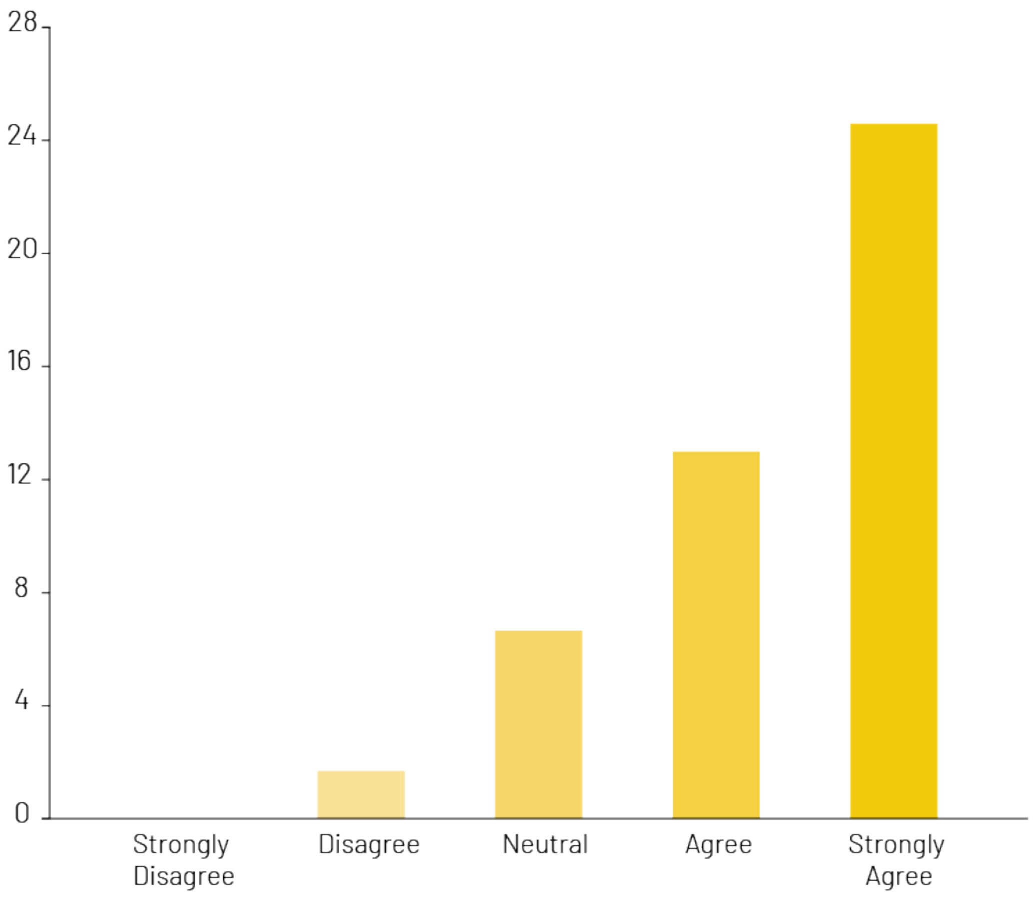
Pork + Grill —> Carcinogens(HCA, PAH) —> Avoid
Description - Carcinogens are cancer-causing compounds
Relative weight of ingredient in the recipe - 58.95%
Decision - Suitable Probability: 1.04 e-18 (~0.0); Not Suitable Probability : 1.0
Source: Cooking & Carcinogens

Overall Recipe Suitability
Suitable Probability: 2.08 e-32 ; Not Suitable Probability: 1.0

Results

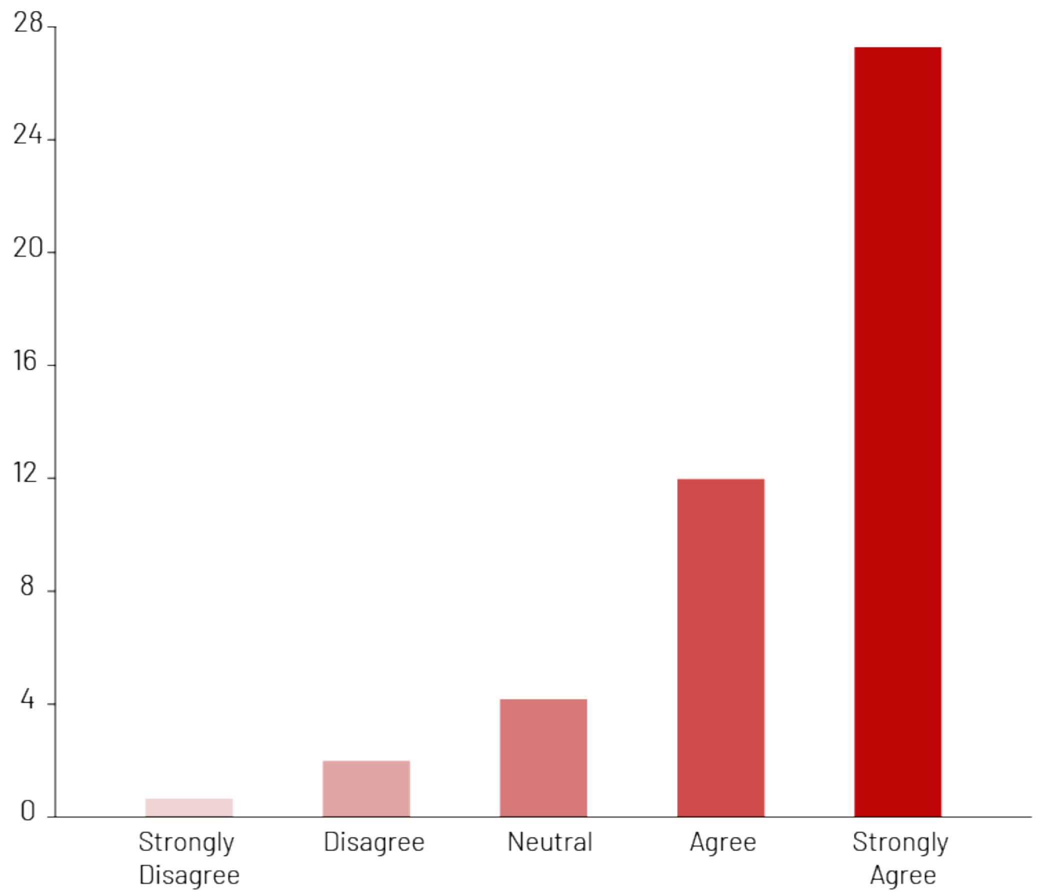


Q1. The explanation was **clear** about why this recipe is recommended as suitable or not suitable for diabetes

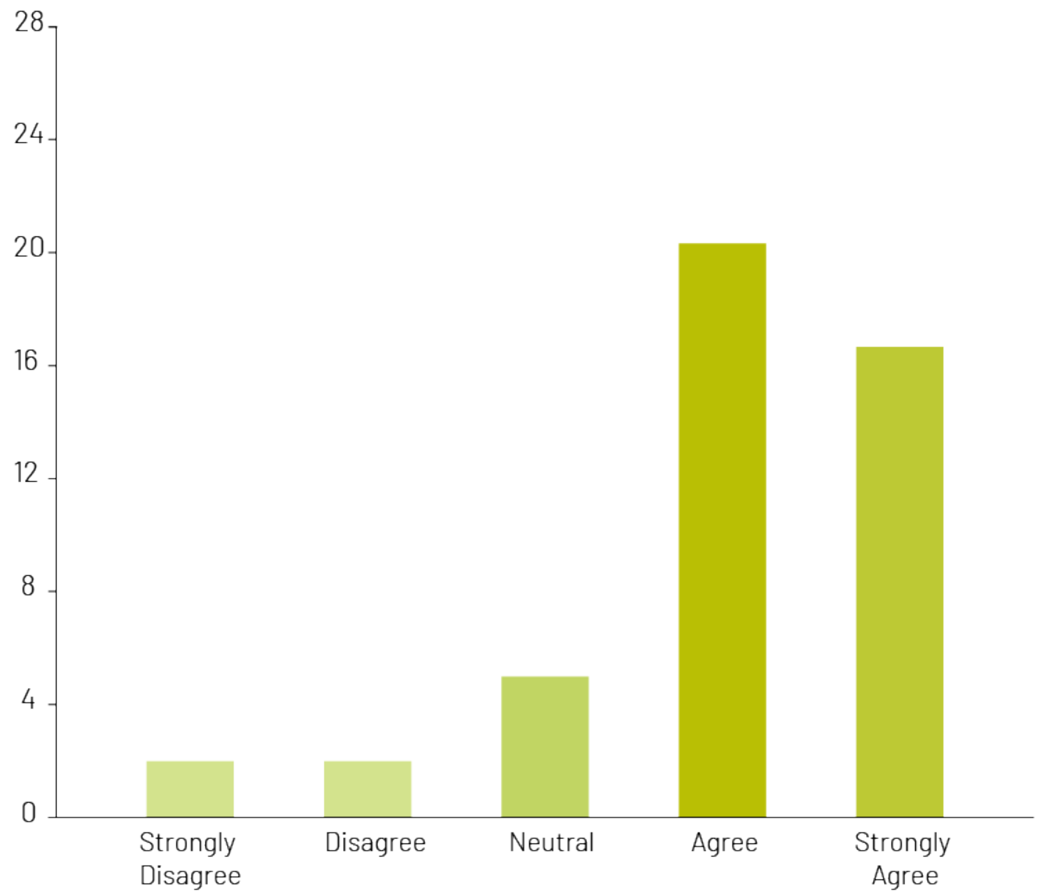


Q2. Explanations and reasons for recommendations were **relevant**

Results



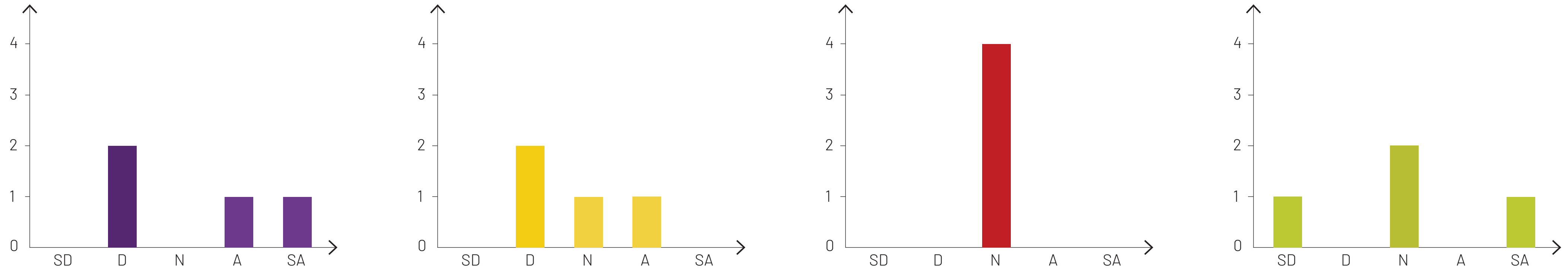
Q3. The explanation provided were **trustworthy** as they can be attributed to a trusted source



Q4. The **format** of the explanation is satisfactory

Domain Expert Results

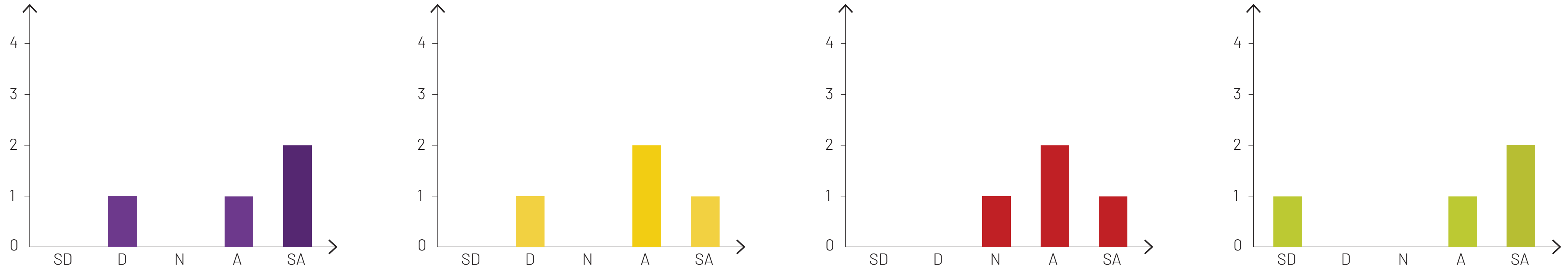
Q1. Clarity | Q2. Relevance | Q3. Trustworthiness | Q4. Format



Grilled Asian Spiced Pork Ribs

+ Alternative when unsuitable

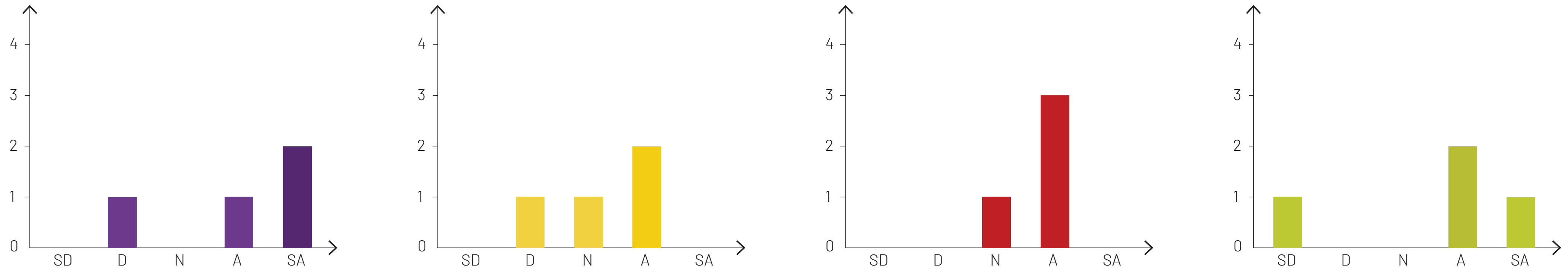
+ One domain expert said they can eat everything in moderation (conflicting with MayoClinic)



Roasted Brussels Sprouts and Butternut Squash

+ 50% or more on agree and strongly agree

+ No major comments



Roasted chicken breasts with herbs de Provence

+ 50% or more on agree and strongly agree

+ No major comments

Chi-Square Test for Independence

Chi-Square Test

+ A statistical test used to determine if there is a significant association between two categorical variables.
+ It compares the observed frequencies in each category with the expected frequencies if the variables were independent (i.e., no association)

Expected Frequency

The frequency we would expect to observe in each category if the null hypothesis is true (e.g., uniform distribution of responses).

Observed Frequency

The actual frequency of responses observed in each category (e.g., how many people chose 1, 2, 3, 4, or 5).

Null Hypothesis

H0: There is no significant difference between observed and expected frequencies (responses are uniformly distributed across the Likert scale).

Alternative Hypothesis

H1: There is a significant difference between observed and expected frequencies (responses are not uniformly distributed).

$p < 0.05$

p-value < 0.05 for all questions: Reject the null hypothesis (H0); there is a statistically significant difference in the distribution of responses (indicating preference towards certain answers).

Summary

RQ1. Entity Extraction using limited ground truth data
TC1: Polynomial-based aggregation for iregular data distrubutions (P2)
TC2: Knowledge-Infused clustering for multimodal retrieval (P1)

RQ2. Elevating process entities to high-order concepts and a structured representation
TC4: A systemic approach to curate and integrate multiple forms of knowledge
TC5: Dynamic Multimodal Process Knowledge Graphs (P3)

RQ3. Explainable recipe process recommendation
TC6: Neurosymbolic recommendation: Knowledge-graph based Bayesian Inferencing, explainable and traceable

RQ4. User Acceptance of Explanations given by the model
Users showed positive sentiment and domain experts were positive about the direction of explanations

P1: Revathy Venkataramanan, Swati Padhee, Saini Rohan Rao, Ronak Kaoshik, Anirudh Sundara Rajan, and Amit Sheth. "Ki-Cook: clustering multimodal cooking representations through knowledge-infused learning." Frontiers in Big Data 6 (2023).

P2: Revathy Venkataramanan, Kaushik Roy, Kanak Raj, Renjith Prasad, Yuxin Zi, Vignesh Narayanan, and Amit Sheth. "Cook-Gen: Robust Generative Modeling of Cooking Actions from Recipes." In 2023 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 981-986. IEEE, 2023.

P3: Revathy Venkataramanan, Chathurangi Shyalika and Amit Sheth. "Dynamic Multimodal Process Knowledge Graphs: A Neurosymbolic Framework for Compositional Reasoning" in IEEE Internet Computing 29, no. 1 (2025): 86-92.

Types of Reasoning

Chain of Evidence Reasoning/ path-based reasoning
Sequence of Premises
Shrimp —> Heart Healthy Item —> Recommend
Shrimp —> High Cholesterol —> Avoid
Inference
Though shrimp is a heart healthy item, it has high cholesterol. Hence recommend with caution

Procedural Reasoning
Procedure
Grilling + Meat —> Traces of Carcinogens
Input
Pork is a Meat
Outcome
Grilling + Pork —> Traces of Carcinogens

Counterfactual Reasoning
Actual Condition
Grilled Chicken (given recipe) is not suitable
Counterfactual Condition
Over Roasted Chicken is a better alternative

Analogical Reasoning
Source
Grilled Chicken
Target
Oven-Roasted Chicken
Inference
Similar ingredients, Similar cooking actions

Explainable AI pipeline recomendation

Why Pipeline Recommendation?

Task: Image Classification

Possible Data Augmentations

CenterCrop(size)
ColorJitter([brightness, contrast, ...])
FiveCrop(size)
Grayscale([num_output_channels])
Pad(padding[, fill, padding_mode])
RandomAffine(degrees[, translate, scale, ...])
RandomApply(transforms[, p])
RandomCrop(size[, padding, pad_if_needed, ...])
RandomGrayscale([p])
RandomHorizontalFlip([p])
RandomPerspective([distortion_scale, p, ...])
RandomResizedCrop(size[, scale, ratio, ...])
RandomRotation(degrees[, interpolation, ...])
Rotate the image by angle.
RandomVerticalFlip([p])
Resize(size[, interpolation, max_size, ...])
TenCrop(size[, vertical_flip])
GaussianBlur(kernel_size[, sigma])
RandomPosterize(bits[, p])
RandomSolarize(threshold[, p])
RandomAdjustSharpness(sharpness_factor[, p])
RandomAutocontrast([p])
RandomEqualize([p])

Possible Models

AlexNet
ConvNeXt
DenseNet
EfficientNet
EfficientNetV2
GoogLeNet
Inception V3
MNASNet
MobileNet V2
MobileNet V3
RegNet
ResNet
ResNeXt
ShuffleNet V2
SqueezeNet
SwinTransformer
VGG
VisionTransformer
Wide ResNet

Possible Optimizers

Adadelta
Adagrad
Adam
AdamW
SparseAdam
Adamax
ASGD
Nadam
Radam
RMSprop
Rprop
SGD

Besides learning rate, each optimizers have their own set of parameters, each with a range of values.

In case of multimodal representation learning, there are various loss functions to choose from

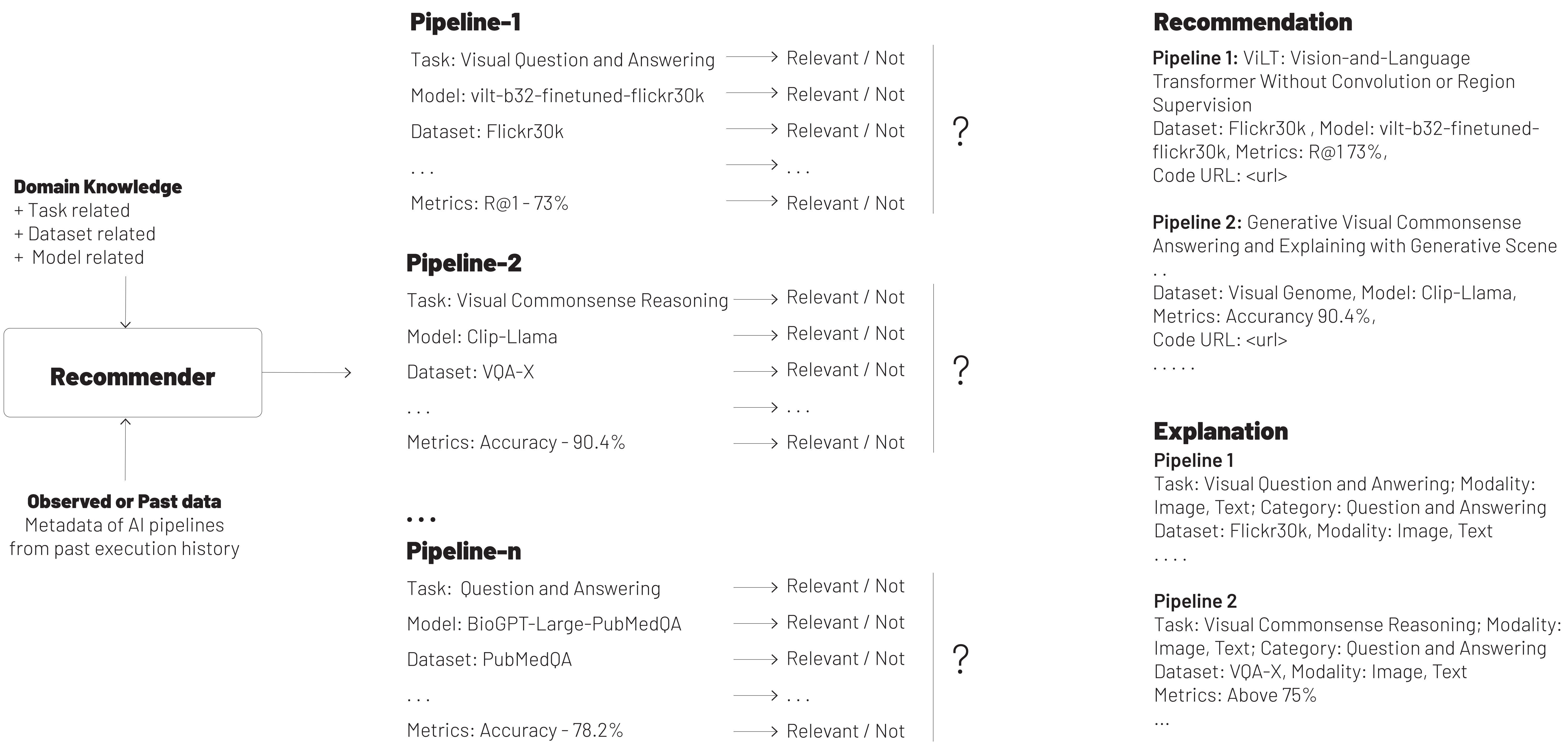
It is costly to test all possible combinations.

How do we choose the optimal set of model and hyperparameters to start our experiments?

Wouldn't it be helpful if a recommender aids us in reducing the search space?

Query

Pipelines executed for visual question and answering using Flickr30k dataset with accuracy above 75%



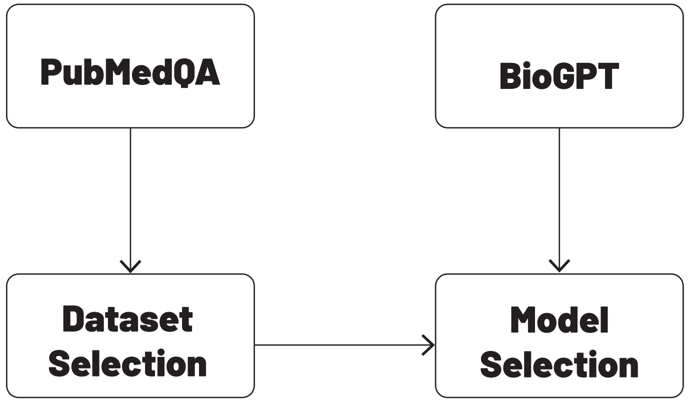
01.

Natural Language Text
To train BioGPT large using the PubMedQA dataset, begin by preprocessing the dataset, which involves tokenization, filtering out irrelevant data ..

02.

Entites
PubMedQA,BioGPT-Large, hyperparameter, preprocessing techniques, task, ...

03.



RQ1

Can the process entities be extracted from unstructured data with limited ground truth data?

Metadata of AI Pipelines

Recipe Text
Peel potatoes, then cut them into thin strips.Heat oil in a deep fryer or skillet. Then fry the potatoes in batches...

Entities
Ingredients: Potato, Oil

Actions: peel, cut, fry,..

?

Entities
Task, Dataset, Model,

Hyperparameters, Metrics, etc

Where can we find the sources for these metadata?

Metadata of AI Pipelines

Recipe Text
Peel potatoes, then cut them into thin strips.Heat oil in a deep fryer or skillet. Then fry the potatoes in batches...

Entities
Ingredients: Potato, Oil
Actions: peel, cut, fry,..

?

Entities
Task, Dataset, Model,
Hyperparameters, Metrics, etc

Where can we find the sources for these metadata?

Metadata Sources

	Papers-with-Code	OpenML	Huggingface	Kaggle	Common Metadata Framework
Pipelines	~ 1 Million	~ 10 Million	~ 1 Million	160,000	
Tasks	~4k	~1.6k	~ 397	~ 200	~ 46
Datasets	12k	3.4k	328k	~ 173k	~45
Models	~ 2k	16k	~ 1 Million	NA	33

Metadata Extraction from API

Papers-with-code

+ Task
+ Dataset
+ Published or Arxiv paper
+ Methods used in the paper
+ Evaluation and Results
+ Github Code repository

OpenML

+ Task
+ Dataset
+ Runs
+ Flow
+ Metrics
+ Parameters

Huggingface

+ Model
+ Dataset
+ Tags
+ Metrics
+ Model Cards

Papers-with-code,
Huggignface

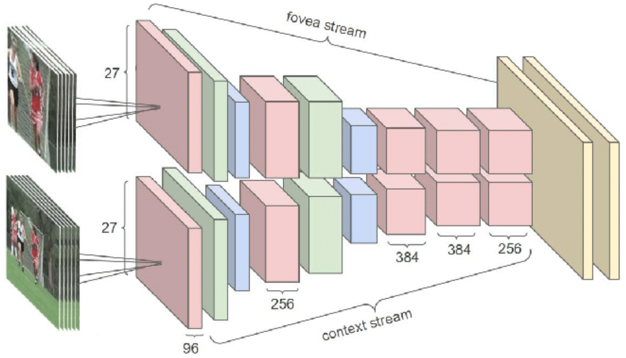
→

Manuscript PDFs

→

Download from Arxiv

→



Metadata Extraction

Papers-with-code
+ Task
+ Dataset
+ Published or Arxiv paper
+ Methods used in the paper
+ Evaluation and Results
+ Github Code repository

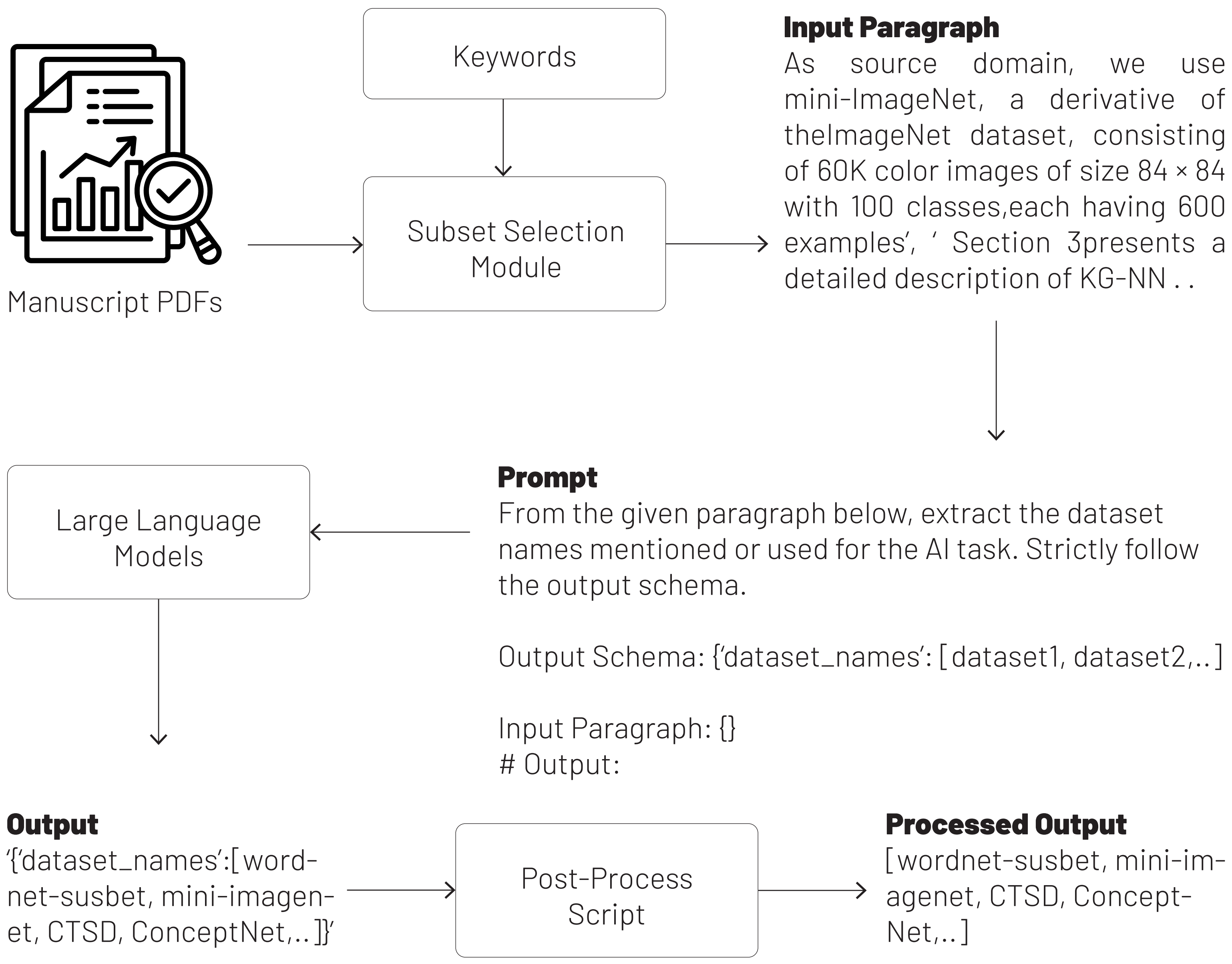
1.3 million papers
User uploads paper and code along with metadata on task, dataset, methods, evaluations and metrics

Missing Explicit Metadata
Task, Dataset, Methods, Evaluation and Results

Proposed Solution
Entity extracttion through knowledge guided promt- ping of large language models

Available Groundtruth
~ 200k datapoints of groundtruth recorded by users which can be used for evaluation

Knowledge-guided prompting of Large Language Models



Revathy Venkataramanan, Aalap Tripathy, Sergey Serebryakov, Suparna Bhattacharya, Annmary Justine, Tarun Kumar, Martin Foltin, Arpit Shah. "AI Pipeline Metadata Knowledge Graph Completion using Pre-trained Large Language Models" (Filed, Under review)

Metadata Extraction Results

	Task	Dataset	Model
Mistral 12B	59.0 %	70.23 %	37.90 %
Gemma 27B	70.90 %	77.81 %	35.90%
Llama 3.3:70B	39.1 %	71.23 %	31.42 %
Chatgpt-4o	80.16 %	80.14 %	57.80 %

Findings

+ Larger models do not always yeild the best results
+ Each model have a sepcific area they are expert at
+ The user input data for models were not good enough which brought our accuracy down

Example

Ground Truth: svm,sftmax

Predicted: Support vector machines, convolutional neural networks, resnet18, densenet2021,..

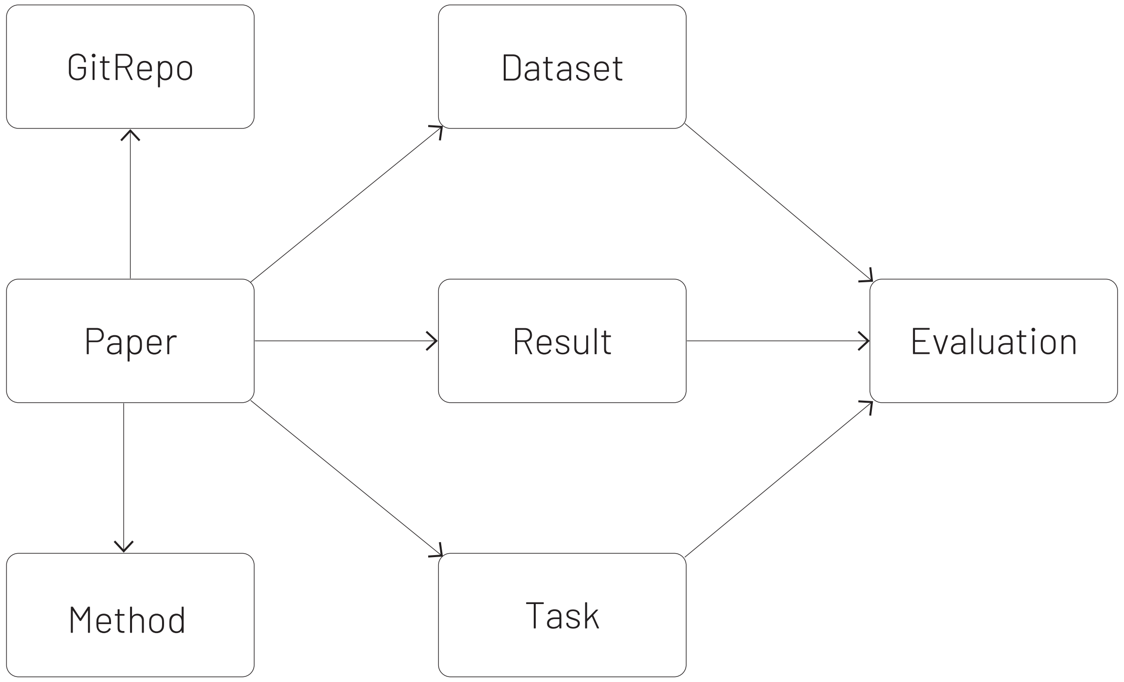
Variation in Metadata

Nomenclature Variation

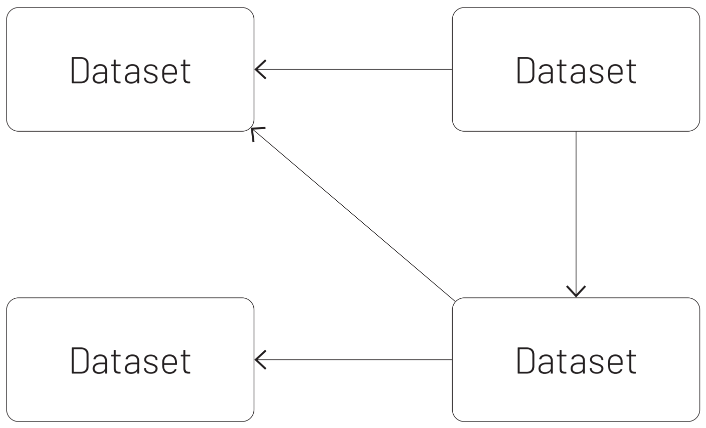
Model

Methods	**Flow**	**Model**
Papers-with-code	OpenML	Huggingface

Datastructure Variation

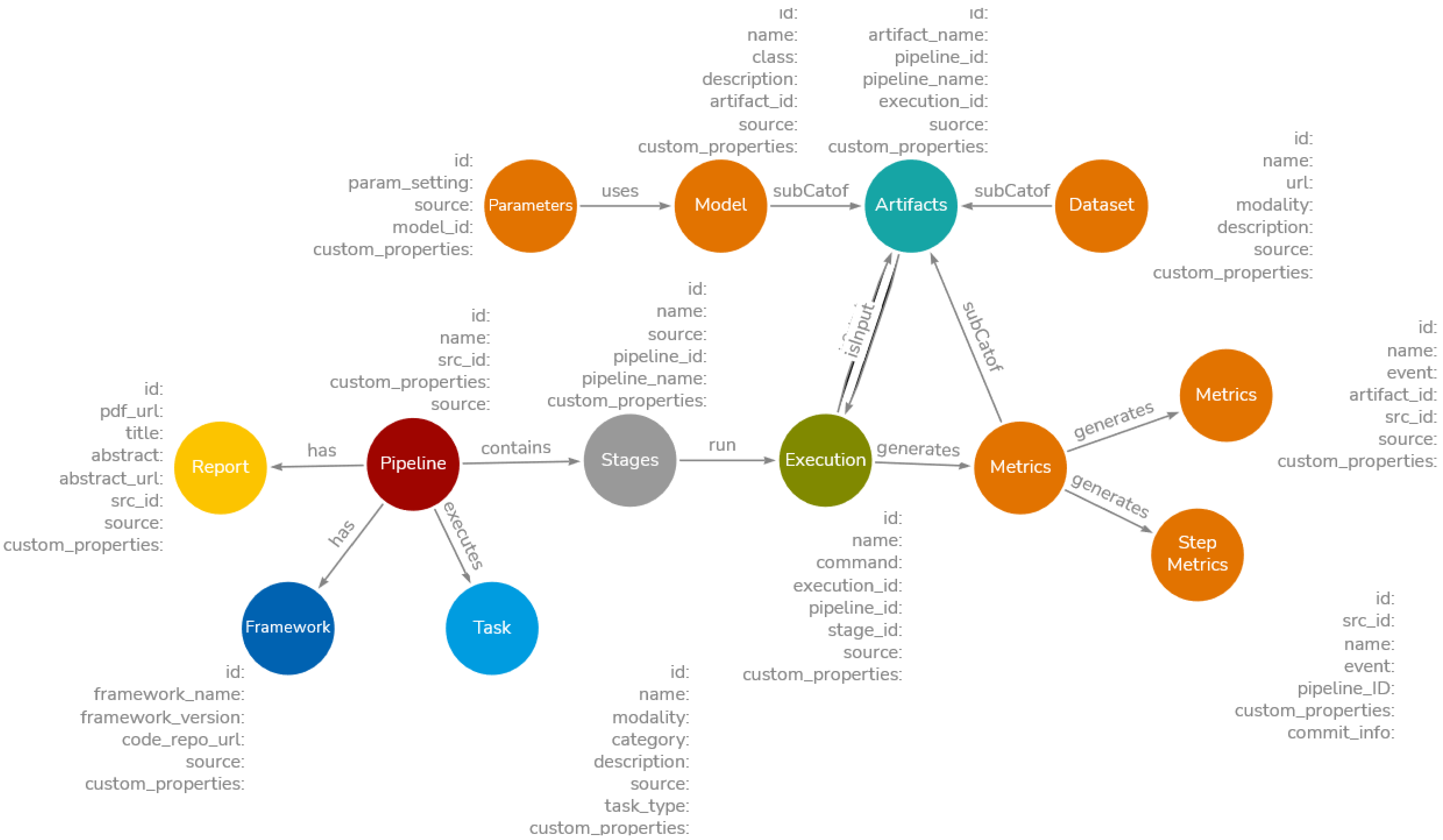


Papers-with-code

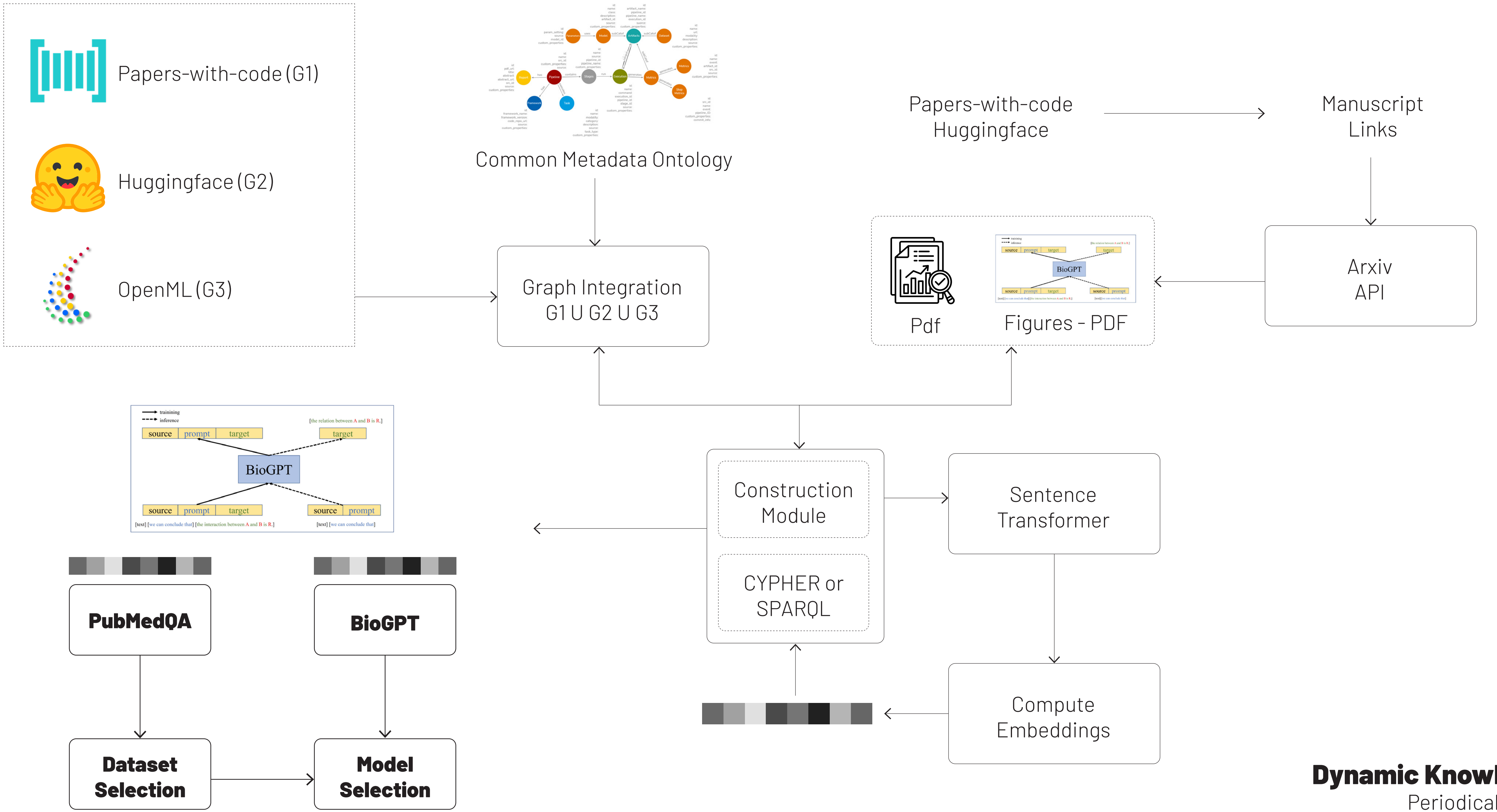


OpenML

Common Metadata Ontology



Construction of AI pipeline Process Graph

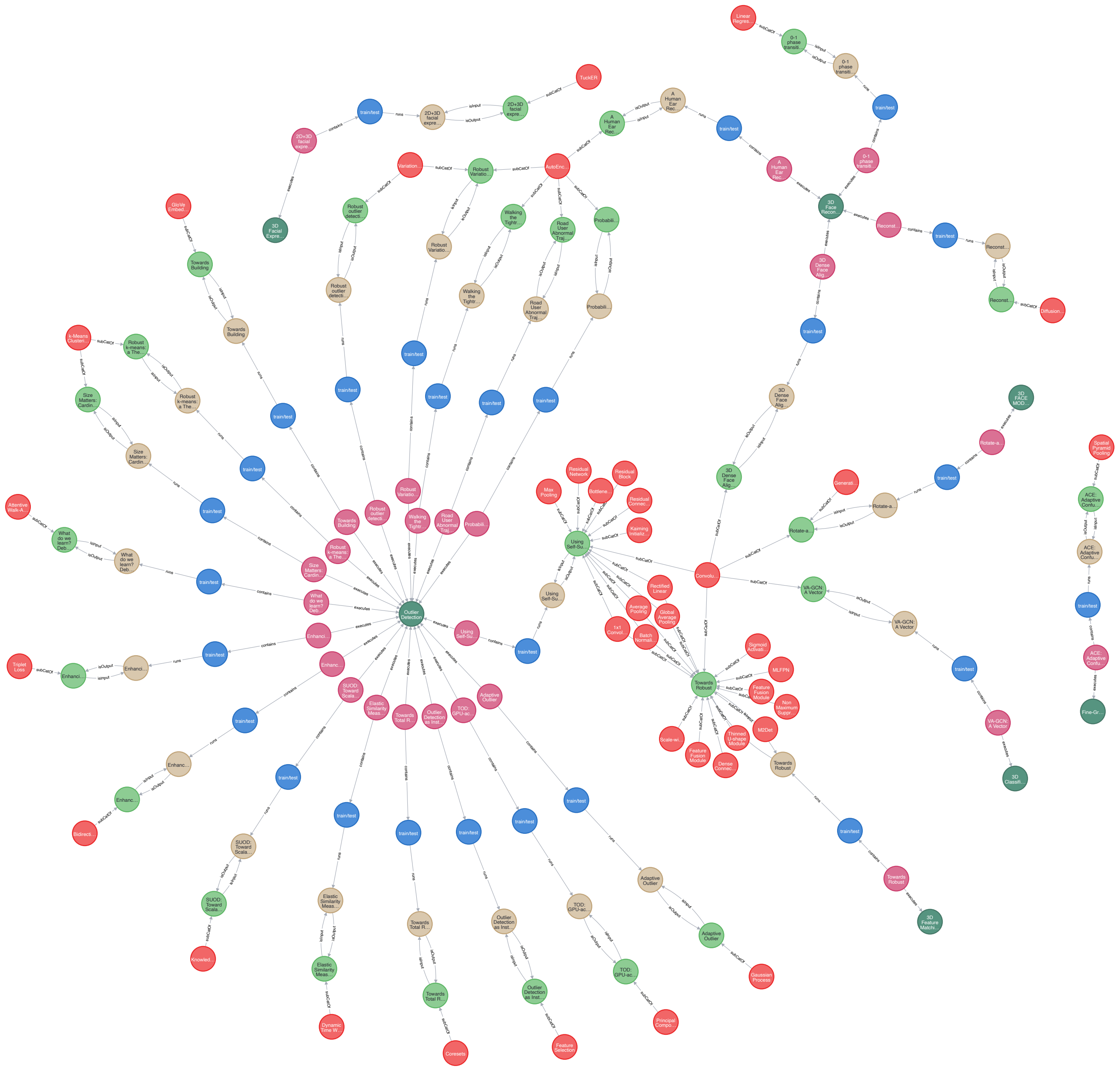


Dynamic Knowledge Repository

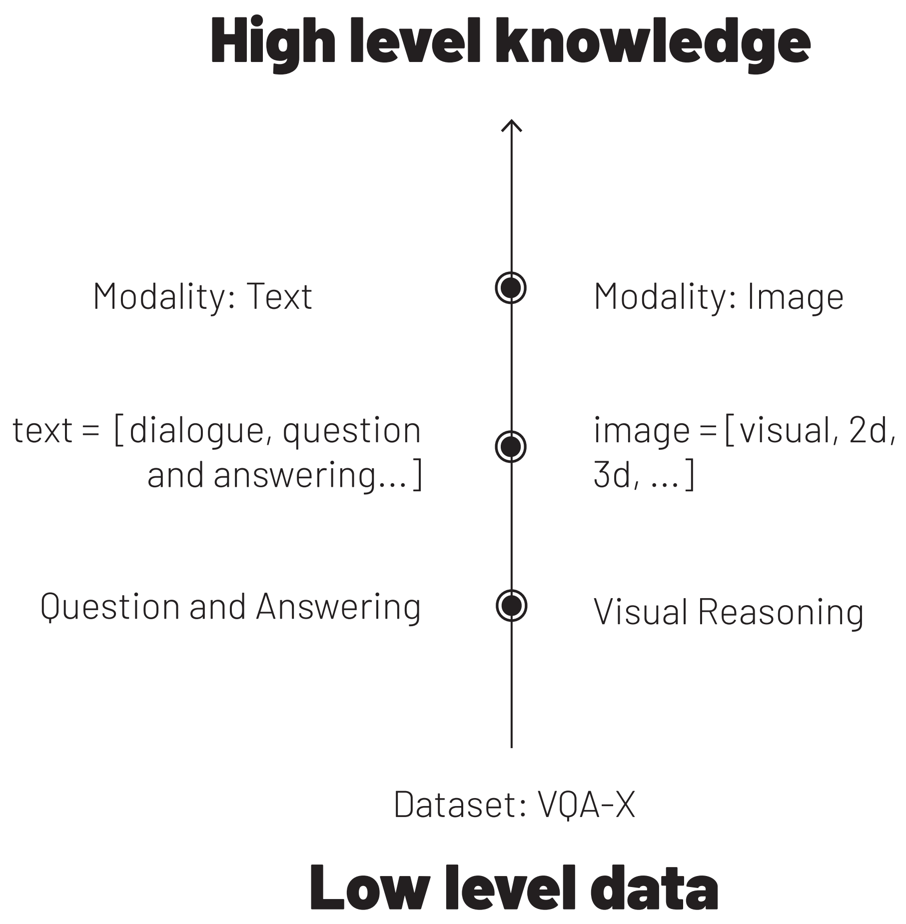
Periodically udpates infromation

AIMKG Overview

Components	Quantity
# Nodes (LPG)	8 Million
# Relationships (LPG)	25 MIllion
# Triples (RDF)	78 Million
# Node types	13
# Relationship Types	15
# Pipelines	1.4 Million



Revathy Venkataramanan, Aalap Tripathy, Tarun Kumar, Sergey Serebryakov, Annmary Justine, Arpit Shah, Suparna Bhattacharya et al. "Constructing a metadata knowledge graph as an atlas for demystifying AI pipeline optimization." Frontiers in Big Data 7 (2025): 1476506.



RQ2

How can process entities be elevated to high-level concepts and represented in a structured format with multimodal data for reasoning?

Knowledge Sources

Knowledge Sources	Type of Information
Published papers from Arxiv, Papers-with-code	Task, Task description, Model, Model description, Dataset, Dataset description, Hyperparameters, Pipeline description
Libraries such as Pytorch, Tensorflow	Model information - model size, type, parameters
Model card from Huggingface	Model information - model size, type, parameters Metrics, Datasets
Readme from Githubs	Model and Dataset information
Kaggle	Datasets

Knoweldge Curation

Task

Modality

image = [visual, 2d, 3d, image,]

text = [dialogue, conversation, sentences,..]

Total Super Class Modalities: 5, Vocabulary size: 64

Category

vocab = [detection, segmentation, localization, recognition, generation, summarization, reasoning, ...]

Total Categories: 73

Description

Each task also has a description from which any other additional information can be gathered as required.

Model

Model Class

Model class information is available for a few models from Huggingface such as:

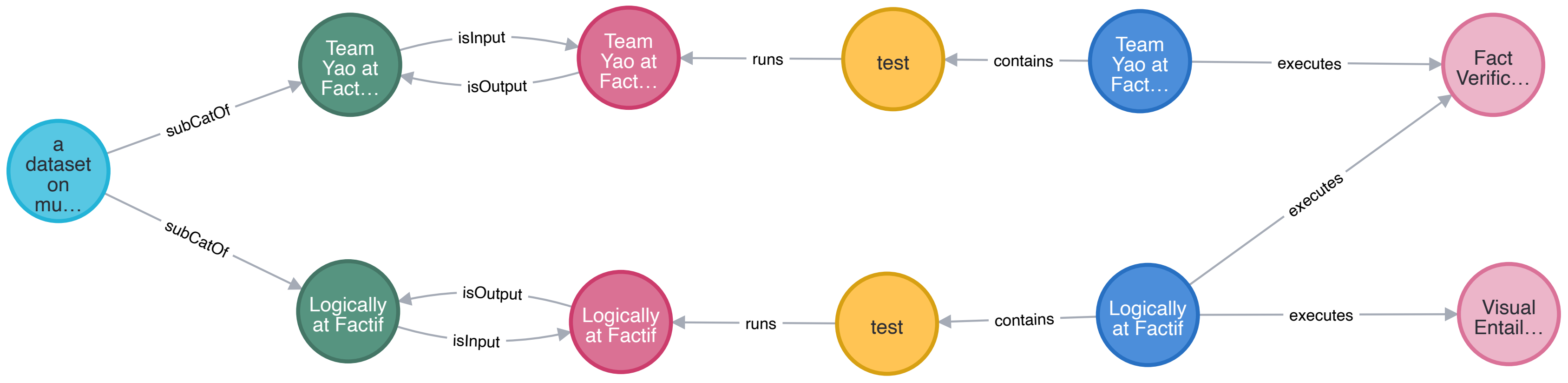
+ Distill-Bert, Bert-base-chinese, Bert-base-NER —> **Class: Bert**

+ Clinical-Llama, Llama3.2-11B-vision-instruct —> **Class: Llama**

Description

Model descriptions detail the domain specific information or training related information

Dataset



Path 1: Factify (Dataset) —> (Artifact) —> (Execution) —> (Stage) —> (Pipeline) —> Fact Verification (Task)

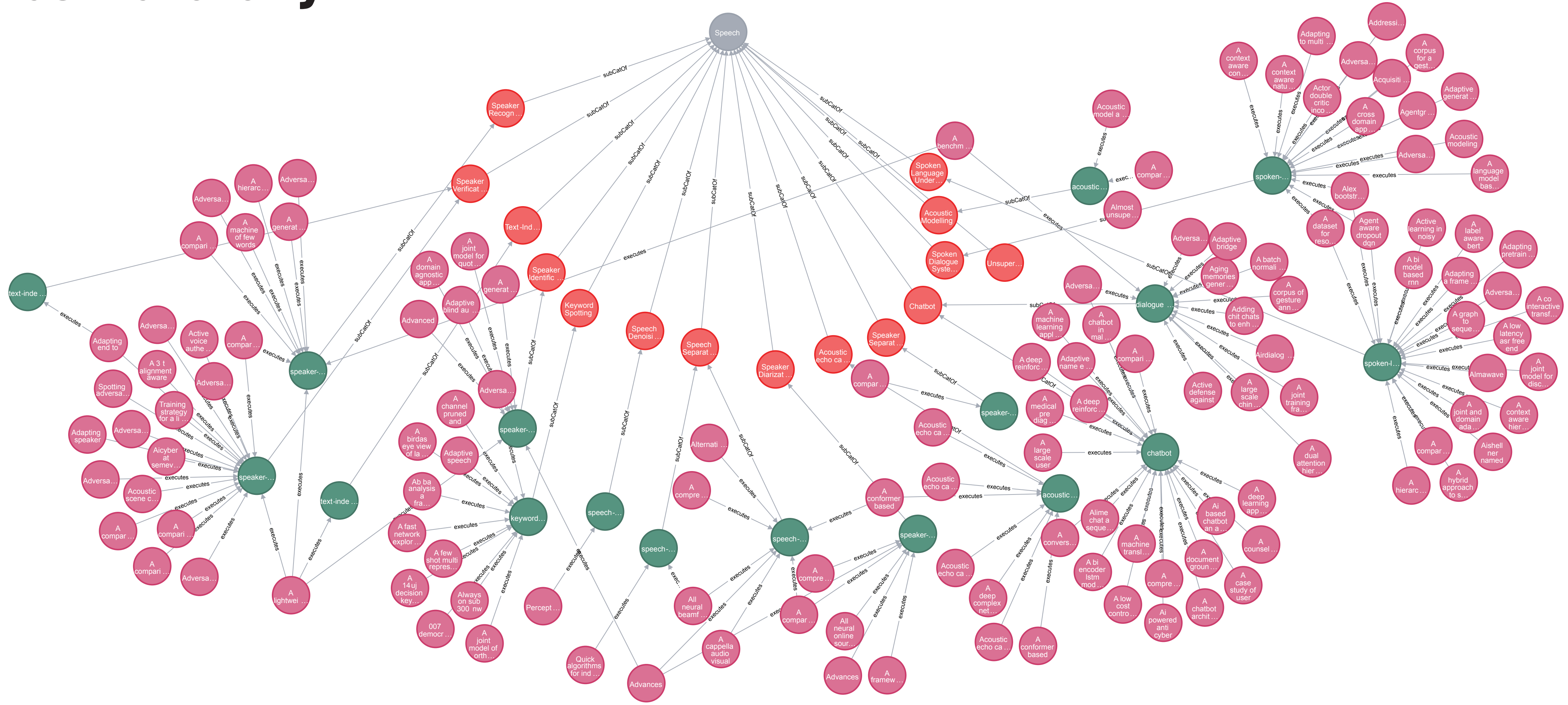
Path 2: Factify (Dataset) — > (Artifact) —> (Execution) —> (Stage) —> (Pipeline) —> Visual Entailment (Task)

The modality of tasks are
Fact Verification - Modality: Text; Visual Entailment - Modality: Image, Multimodal

Therefore, the modality of the dataset Factify is,
Factify - Modality: Text, Image, Multimodal

Knoweldge Curation

Task Taxonomy



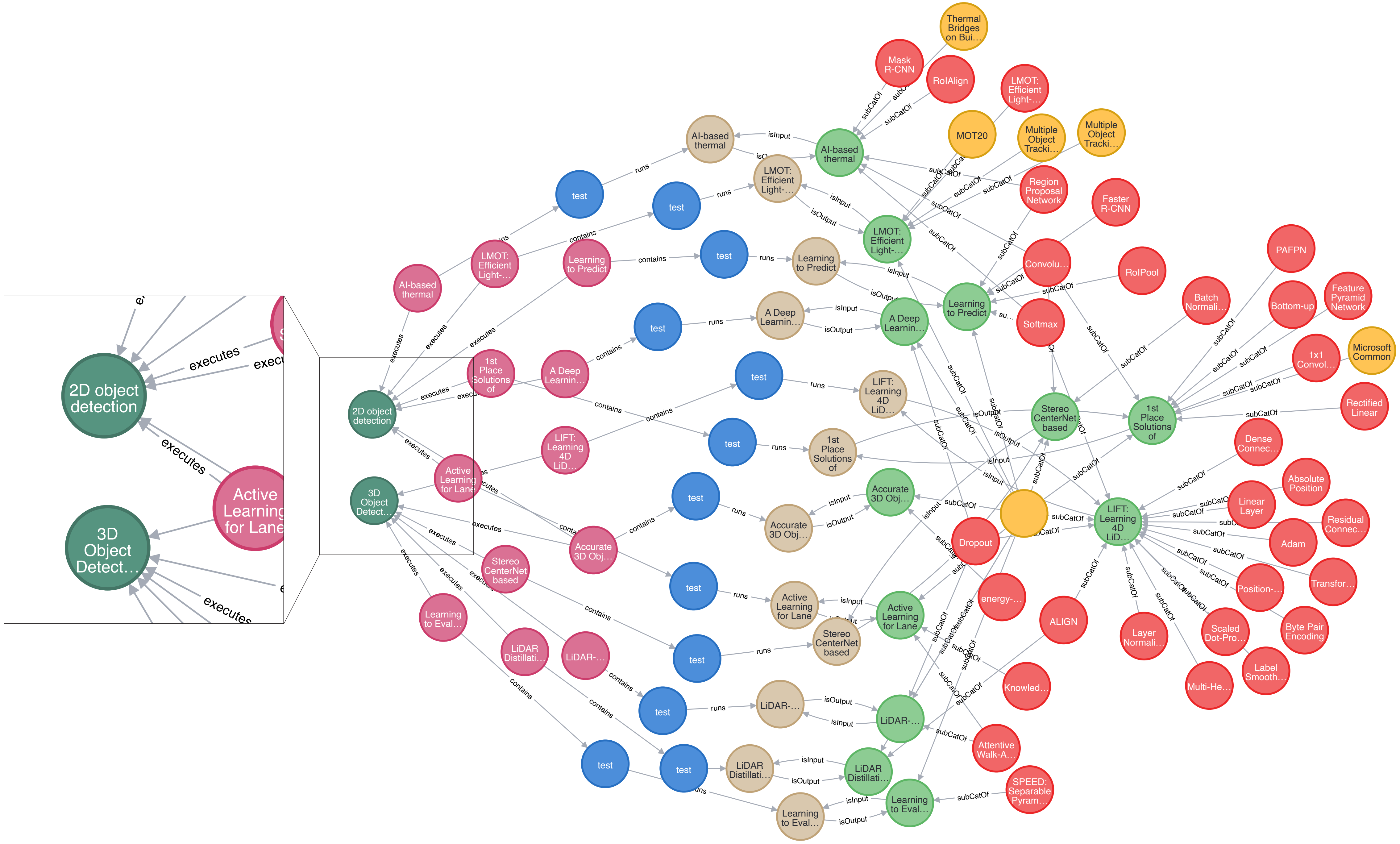
Root (Eg: Speech)

Super Class of Tasks (Eg:Speaker Verification)

Tasks (Text Dependent Speaker Verification)

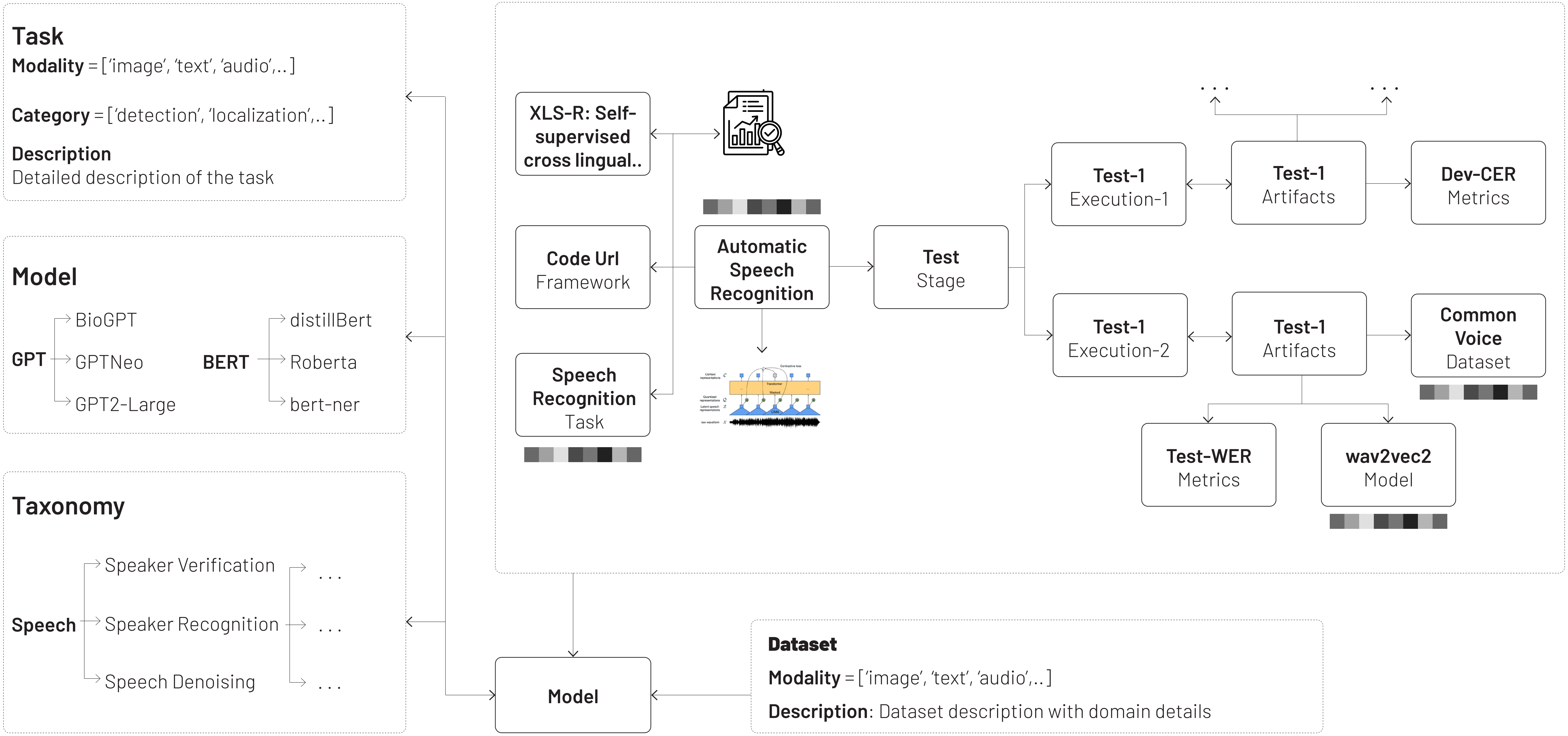
Pipelines (Eg: 1. On Bottleneck Features for Text-Dependent Speaker Verification Using X-vectors, 2. End-to-End Attention based Text-Dependent Speaker Verification)

Benefits of Grounding



Query - List all the pipelines with dataset and model for image detection task

Dynamic Multimodal Process Knowledge Graph for AI Pipelines



Query

Pipelines executed for visual question and answering using Flickr30k dataset with accuracy above 75%

Explainable Recommendation

Pipeline 1
Task: Visual Question and Anwering; Modality: Image, Text; Category: Question and Answering
Dataset: Flickr30k, Modality: Image, Text
. . . .

Pipeline 2
Task: Visual Commonsense Reasoning; Modality: Image, Text; Category: Question and Answering
Dataset: VQA-X, Modality: Image, Text
Metrics: Above 75% . . .

RQ3

How can explainable recommendation results be produced that are supported by reasoning and can be traced back to trusted sources?

Neurosymbolic Heuristic Ranking Function

Recommendation 1: Combination of embedding (neural) and set similarity of semantic properties (symbolic)

$$\mathrm{sim}(t_i, t_j) = \frac{\overbrace{\mathrm{cos\_sim}(e_i, e_j)}^{\text{Neural}} + \overbrace{J(t_i, t_j) + J(\mathrm{cat}_i, \mathrm{cat}_j) + J(\mathrm{mod}_i, \mathrm{mod}_j)}^{\text{Symbolic}}}{n}$$

$$\mathrm{sim}(d_i, d_j) = \frac{\mathrm{cos\_sim}(e_i, e_j) + J(d_i, d_j) + J(\mathrm{modi}, \mathrm{modj})}{n}$$

$$\mathrm{sim}(m_i, m_j) = \frac{\mathrm{cos\_sim}(e_i, e_j) + J(t_i, t_j) + J(\mathrm{class}_i, \mathrm{class}_j)}{n}$$

Neural

Embeddings are effective at capturing synonyms and identifying words with similar meanings due to their pattern mining abilities

Example: dialogue vs coversation

ing_i → **SentenceTransformer** (all-mpnet-base-v2) → e_i

Symbolic

Semantic properties computed for pipeline entities to enable higher-order reasoning

Example: MS-COCO - Image dataset, PubMedQA - Test Dataset

J - Jaccard Similarity of tokens

Mod - modality

Cat - category

N- normalizing factor

e - embedding of entity names created using pretrained sentence transformer all-mpnet-base-v2

Neurosymbolic Heuristic Ranking Function Results

Areas	AIMKG	MLS-KG
Computer Vision	17 / 20	8 / 20
Natural Lanugage Processing	16 / 20	10 / 20
Audio / Speech	15 / 20	11 /20
Video	15 / 20	10 / 20
Multimodal	6 / 10	6 / 10
Other	9 / 10	6/ 10
Total	78 / 100	51 / 100

AIMKG - AI Pipeline Metadata Knowledge Graph

MLS-KG - Machine Learning Schema based Knowledge Graph

Evaluation

+ Given a query task, identify similar tasks and its pipelines. Recommend top-3 tasks and its pipelines
+ Users evaluate if any of these are relevant to the input query

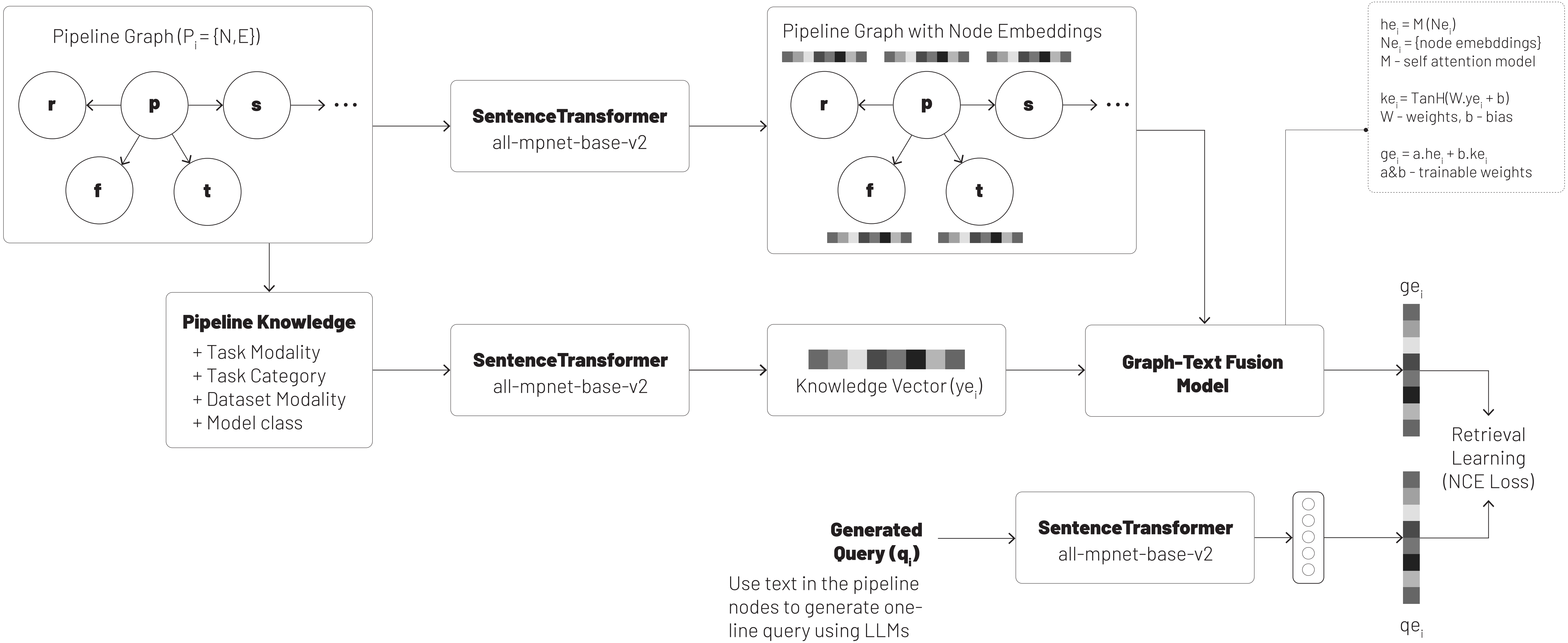
Findings

+ CV and NLP had sufficient pipelines to return relevant results for more query
+ Multimodal pipelines are reletively less with short population pool to return relevant results
+ MLS-KG had insufficient semantic properties, resulted in less relevant results. That is, semantic properties played a vital role!

Revathy Venkataramanan, Aalap Tripathy, Tarun Kumar, Sergey Serebryakov, Annmary Justine, Arpit Shah, Suparna Bhattacharya et al. "Constructing a metadata knowledge graph as an atlas for demystifying AI pipeline optimization." Frontiers in Big Data 7 (2025): 1476506.

Knowledge-enabled Graph-Text Fusion Model

Recommendation 2: Natural Lanuguage Queries



Knowledge-enabled Graph-Text Fusion Model: Results

Models	R1	R3	R5
Random	0.2	0.5	0.6
GAT	44.3	69	66.2
GCN	48.4	62.8	69
Sent_Trans	57.6	66.8	70.7
Sent_Trans_FT	69.0	79.6	83.6
GT-Fusion	74.8	82.7	85.8
K-GT-Fusion	**76.3**	**85.4**	**87.7**

Experiment Set up

+ 10,000 pipelines, 8k training, 2k testing
+ 2 queries per pipeline, randomly chosen
+ R1 - retrieval at 1, R3 - retrieval in top-3, R5- retrieval in top 5

Findings

+ Just text or just graph was not sufficient
+ Graph networks prioritize topology
+ Pipeline graphs have very similar topology
+ Rich text information in the nodes
+ Infusing knowledge yielded better results

Revathy Venkataramanan, Aalap Tripathy, Tarun Kumar, Sergey Serebryakov, Annmary Justine, Arpit Shah, Suparna Bhattacharya et al. “Constructing a metadata knowledge graph as an atlas for demystifying AI pipeline optimization.” Frontiers in Big Data 7 (2025): 1476506.

Comparison with ChatGPT

ChatGPT Results

Input Prompt: Create a session where you are an AI pipeline recommender. I will request for a pipeline that has been executed in the past. You can use any source you want. For example, when I request to recommend a pipeline for "3d video object tracking", I expect a response as follows: Similar Task Name: 3D Object Tracking, Similarity: 0.6083, Piplines: Exploring Point-BEV Fusion for 3D Point Cloud Object Tracking with Transformer, URL: https://arxiv.org/pdf/2208.05216v1.pdf, Model: Transformer, Dataset: KITTI, Github: https://github.com/jasonkks/pttr Piplines: MOTSLAM: MOT-assisted monocular dynamic SLAM using single-view depth estimation, URL: https://arxiv.org/pdf/2210.02038v1.pdf, Model: SLAM, Dataset: KITTI, Github: <url>. Now give me the pipelines executed for supervised anomaly detection.

Response: Similar Task Name: Supervised Anomaly Detection, Similarity: 0.7254

1) Paper Title: "DeepOne-Class: Outlier Detection with Deep Learning", URL: https://arxiv.org/abs/1802.06360, Model: Deep Neural Networks, Dataset: Credit Card Fraud, NAB, Github: https://github.com/hpzhao/Anomaly-Detection-DeepOneClass

2) Paper Title: "Autoencoder-Based Anomaly Detection", URL: https://arxiv.org/abs/1802.06360, Model: Autoencoder, Dataset: MNIST, CIFAR-10, Github: https://github.com/abnormal-1/anomaly- detection-resources

3) Paper Title: "LSTM-based Encoder-Decoder for Anomaly Detection", URL: https://arxiv.org/abs/1802.06360, Model: Long Short-Term Memory (LSTM), Dataset: Time Series Anomaly Detection Benchmark, Github: https://github.com/ChunFan-AST/LSTM Anomaly Detection

Findings

+ All github returned 404

+ All three papers, arxiv link is the same; does not belong to any papers recommended

+ Paper-1 does not exist and therefore all the following information is not true

+ Datasets mentioned in paper-2 and paper-3 are not datasets used in the paper (for whatever paper the arxiv link points to)

Comparison with ChatGPT

AIMKG Results

Input Query: Supervised Anomaly Detection

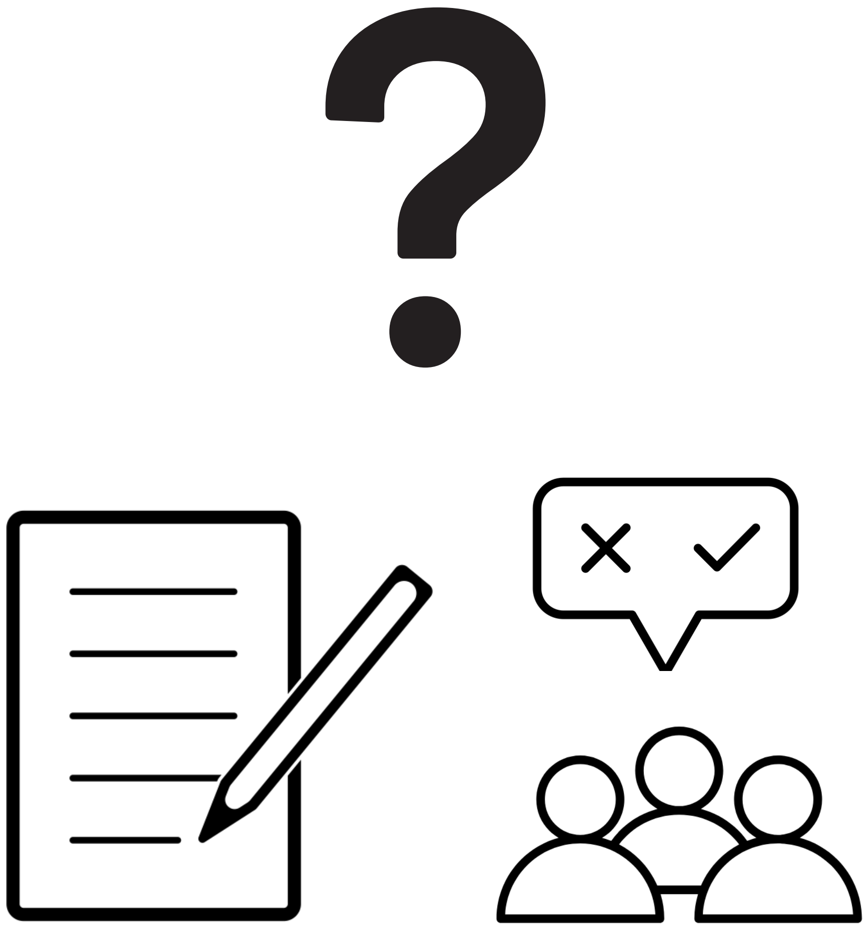
Since the exact match is not found, we recommend the following pipelines from relevant task:

Recommendation 1:
Similar Task Name: Weakly Supervised Defect Detection
Similarity: 0.4752
Pipline-1: S2D2Net: An Improved Approach For Robust Steel Surface Defects Diagnosis With Small Sample Learning, URL: https://ieeexplore.ieee.org/document/9506405, Git: https://github.com/vikxoxo/S2D2Net
Pipline-2: Mixed supervision for surface-defect detection: from weakly to fully supervised learning, URL: https://arxiv.org/pdf/2104.06064v3.pdf, Git: https://github.com/aws-samples/amazon-sagemaker-edge-defect-detection-computer-vision
. . .

Recommendation 2:
Similar Task Name: Semi-supervised Anomaly Detection
Similarity: 0.4643
Pipline-1: Deep Semi-Supervised Anomaly Detection, URL: https://arxiv.org/pdf/1906.02694v2.pdf, Git: https://github.com/Fraunhofer-AISEC/R2-AD2
. .

+ All the papers exist, corresponding arxiv links and github repositories

+ Datasets, models and metrics are available but not included for brevity



RQ4

Do the users accept the explanations given by the system interms of clarity, relevance, trustworthiness and format?

User Evaluation Study

Hypothesis 1
Does the user perceive the explanation as sufficiently clear to determine the relevance of the recommendation?

Hypothesis 2
Does the user find the explanation provided by the system to be trustworthy?

Number of Participants - 37
Number of Queries - 3
Method of Evaluation - Survey, 4 questions/Recipe
Type of answers - 5 point Likert scale

Query Task: Conversation Generation

Recommendations
Since the exact match of the task is not found, the pipelines were recommended based on similar tasks below:

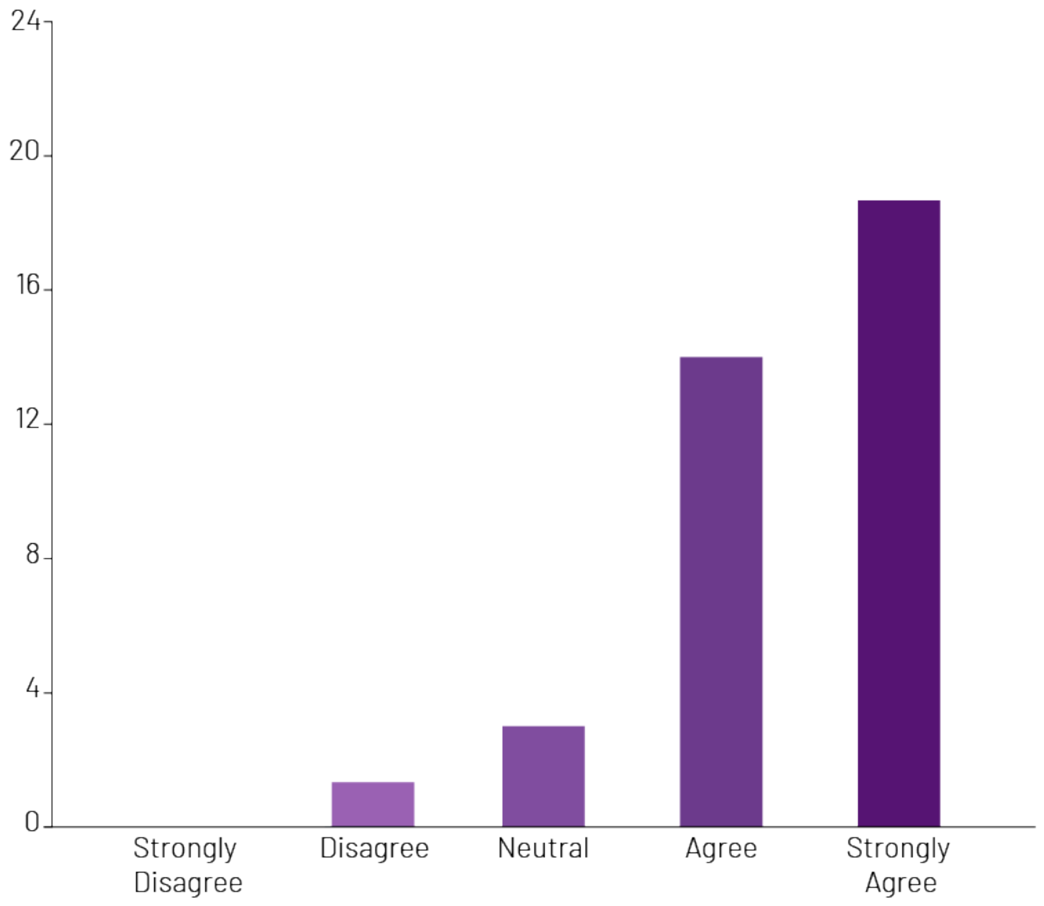
Recommendation1
Similar task: Dialogue understanding
Similarity score:0.6683

Explanation
Query Task Type: Text
Recommended Task Type: Text
Query Task Category: Understanding
Recommended Task Category: Understanding

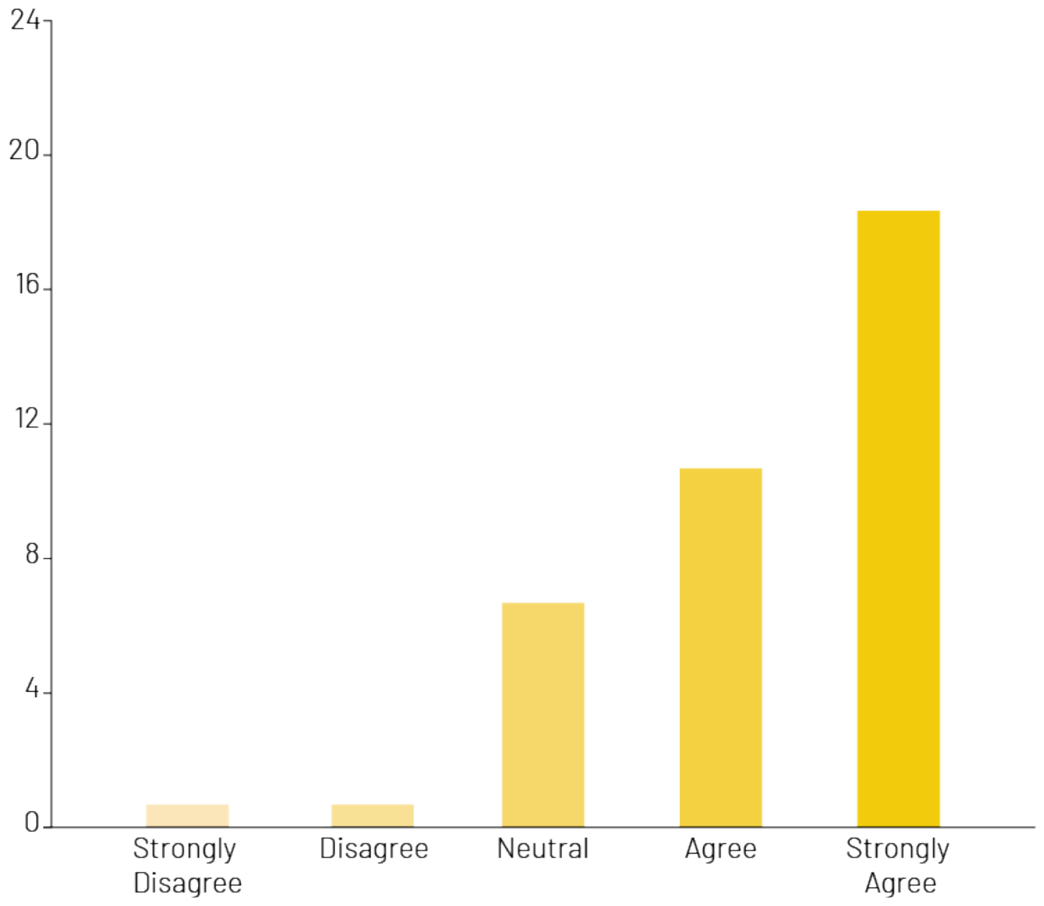
Pipeline1: Adding Chit-Chat to Enhance Task-Oriented Dialogues
Report URL: https://arxiv.org/pdf/2010.12757v2.pdf
Code URL: https://github.com/facebookresearch/accentor

Pipeline2: A Benchmark for Automatic Medical Consultation System: Frameworks, Tasks and Datasets
Report URL: https://arxiv.org/pdf/2204.08997v2.pdf
Code URL:https://github.com/lemuria-wchen/imcs21

Results

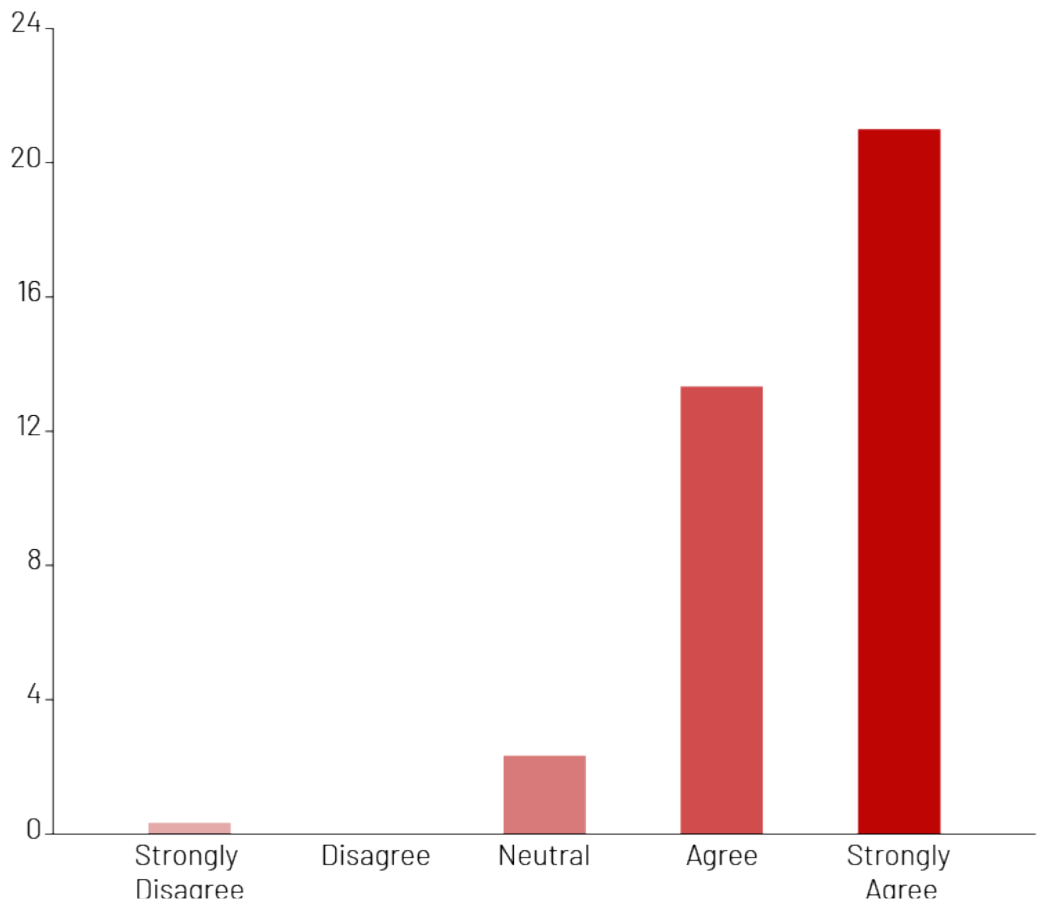


Q1. The explanation was **clear** about why this particular pipeline was recommended for the given query task

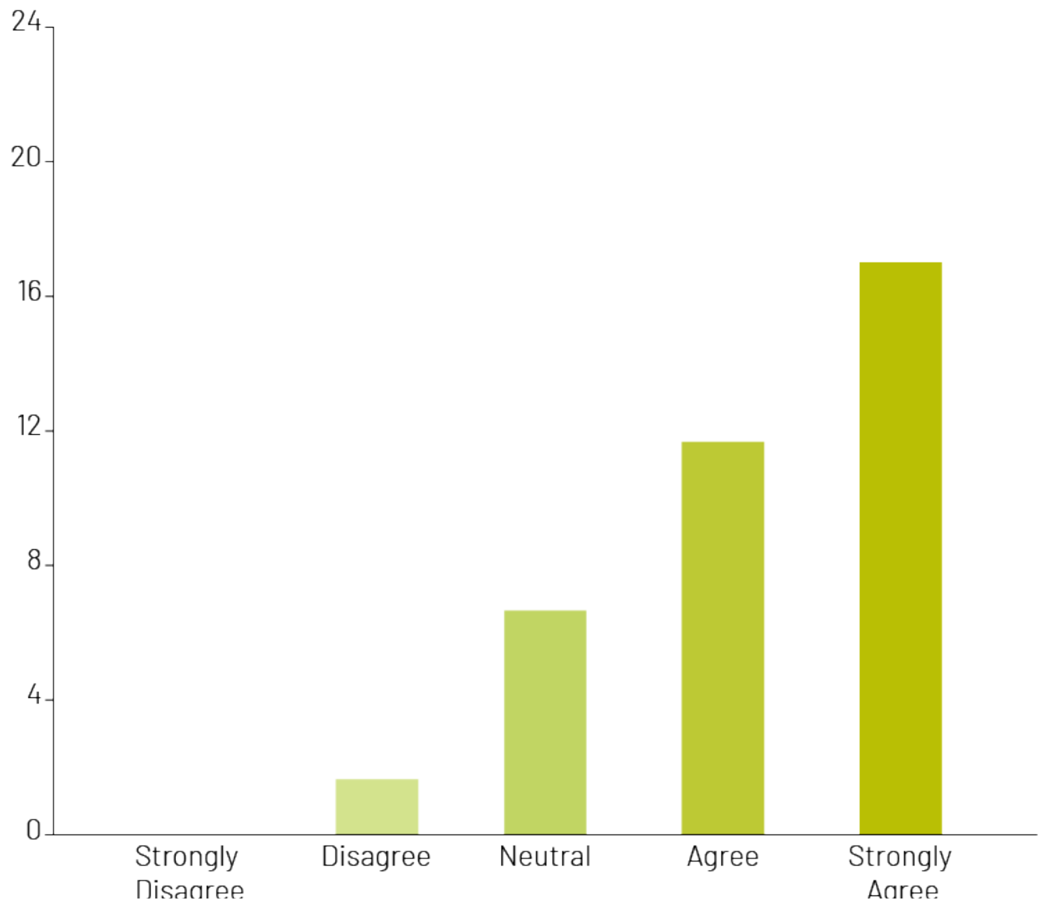


Q2. Explanations for the recommended AI pipelines were **relevant**

Results



Q3. The explanation provided were **trustworthy** as they can be attributed to a trusted source



Q4.. The **format** of the explanation is satisfactory

Chi-Square Test for Independence

Chi-Square Test

+ A statistical test used to determine if there is a significant association between two categorical variables.
+ It compares the observed frequencies in each category with the expected frequencies if the variables were independent (i.e., no association)

Expected Frequency

The frequency we would expect to observe in each category if the null hypothesis is true (e.g., uniform distribution of responses).

Observed Frequency

The actual frequency of responses observed in each category (e.g., how many people chose 1, 2, 3, 4, or 5).

Null Hypothesis

H0: There is no significant difference between observed and expected frequencies (responses are uniformly distributed across the Likert scale).

Alternative Hypothesis

H1: There is a significant difference between observed and expected frequencies (responses are not uniformly distributed).

$p < 0.05$

p-value < 0.05 for all questions: Reject the null hypothesis (H0); there is a statistically significant difference in the distribution of responses (indicating preference towards certain answers).

Summary

RQ1. Entity Extraction using limited ground truth data

TC3: Knowledge-guided prompting of LLMs to exact entities from manuscripts (P4)

RQ2. Elevating process entities to high-order concepts and a structured representation

TC4: A systemic approach to curate and integrate multiple forms of knowledge (P4)

TC5: Dynamic Multimodal Process Knowledge Graphs (P3)

RQ3. Explainable recipe process recommendation

TC7: Neurosymbolic heuristic ranking function (P4)

TC8: Knowledge-enabled Graph-Text Fusion model (P4)

RQ4. User Acceptance of Explanations given by the model

Users showed positive sentiment towards clarity, relevancy, trusworthiness and format of explanations

P3: Revathy Venkataramanan, Chathurangi Shyalika and Amit Sheth. "Dynamic Multimodal Process Knowledge Graphs: A Neurosymbolic Framework for Compositional Reasoning" in IEEE Internet Computing 29, no. 1 (2025): 86-92.

P4: Revathy Venkataramanan, Revathy Venkataramanan, Aalap Tripathy, Tarun Kumar, Sergey Serebryakov, Annmary Justine, Arpit Shah, Suparna Bhattacharya et al. "Constructing a metadata knowledge graph as an atlas for demystifying AI pipeline optimization." Frontiers in Big Data 7 (2025): 1476506.

P5: Revathy Venkataramanan, Revathy Venkataramanan, Aalap Tripathy, Martin Foltin, Hong Yung Yip, Annmary Justine, and Amit Sheth. "Knowledge Graph Empowered Machine Learning Pipelines for Improved Efficiency, Reusability, and Explainability." IEEE Internet Computing 27, no. 1 (2023): 81-88.

Types of Reasoning

Analogical Reasoning

Source

Task: Visual Question and Answering

Target

Similar Task: Visual Commonsense Reasoning

Inference

Modality: Image, Text

Category: Question and Answering (Vocabulary + Taxonomy)

Conclusion

Dynamic Multimodal Process Knowledge Graph

+ Neurosymbolic Framework
+ Moving beyond from embedding only representation
+ Embedding (neural) + Domain knowledge (symbolic) representation
+ Explainable decision making
+ Traceability
+ Can do multimodal reasoning

Neural
Embeddings for pattern mining to extract relevant entities to form structured data

Symbolic
Higher-order reasoning and decision making abilities of Knowledge Graphs

01.

RQ1. Entity Extraction using limited ground truth data

TC1: Polynomial-based aggregation for iregular data distrubutions (P2)

TC2: Knowledge-Infused clustering for multimodal retrieval (P1)

TC3: Knowledge-guided prompting of LLMS (P4)

02.

RQ2. Elevating process entities to high-order concepts and a structured representation

TC4: A systemic approach to curate and integrate multiple forms of knowledge (part in P4)

TC5: Dynamic Multimodal Process Knowledge Graphs (P3)

03.

RQ3. Explainable recipe process recommendation

TC6: Neurosymbolic recommendation: Knowledge-graph based Bayesian Inferencing

TC7: Neurosymbolic heuristic ranking function (P4)

TC8: Knowledge-enabled Graph-Text Fusion model (P4)

04.

RQ4. User Acceptance of Explanations given by the model

For both the domain, the users showed positive sentiment towards clarity, relevancy, trusworthiness and format of explanations

Domain Contributions: Recipes

01. Cooking Action Extraction

CookGen, a ploynomial aggregation based approximation model and benchmark dataset for cooking action extraction

02. Disease-specific Knowledge Graph

Diabetes disease specific knowledge graph that reasons on USFDA ingredients can promote further research in this area

03. Neurosymbolic Recommendation

Knowledge graph based bayesian for recipe recommendation where the reasons and explanations can be traced back to trusted sources

04. Explainable & Traceable Reasoning

Methods to perform different kinds of reasoning while producing explanations for recommendation along with source information

Domain Contributions: AI Pipelines

01. Common Metadata Ontology

First-of-a-kind metadata ontology for end-to-end AI pipelines built on the foundations of Common Metadata Framework (CMF)

02. AI Pipeline Metadata Knowledge Graph

Large scale first-of-a-kind AI pipeline Metadata KNowledge Graph with 1.6 million pipelines that enables search and discoverability of 10k tasks, 53k datasets and 280k models

03. Explainable Recommendation

AI pipeline recommendation methods that can be traced back to the sources or code repositories to ensure reproducibility of AI pipelines

04. Knowledge Guided Prompting

Knowledge guided prompting of LLMs to extact metadata from semi-strucutred documents

Publications

Recipe Recommendation

+ **Revathy Venkataramanan,** Swati Padhee, Saini Rohan Rao, Ronak Kaoshik, Anirudh Sundara Rajan, and Amit Sheth. "Ki-Cook: clustering multimodal cooking representations through knowledge-infused learning." Frontiers in Big Data 6 (2023).

+ **Revathy Venkataramanan,** Kaushik Roy, Kanak Raj, Renjith Prasad, Yuxin Zi, Vignesh Narayanan, and Amit Sheth. "Cook-Gen: Robust Generative Modeling of Cooking Actions from Recipes." In 2023 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 981-986. IEEE, 2023.

+ **Revathy Venkataramanan,** Chathurangi Shyalika and Amit Sheth. "Dynamic Multimodal Process Knowledge Graphs: A Neurosymbolic Framework for Compositional Reasoning" in IEEE Internet Computing 29, no. 1 (2025): 86-92.

+ Priyadharsini Ramamurthy, Vishal Pallagani, Vedant Khandelwal, **Revathy Venkataramanan**, Kausik Lakkaraju, Sathyanarayanan N. Aakur, and Biplav Srivastava. "A Rich Recipe Representation as Plan to Support Expressive Multi-Modal Queries on Recipe Content and Preparation Process." International Conference on Automated Planning and Scheduling (2022).

+ Amit Sheth, Manas Gaur, Kaushik Roy, **Revathy Venkataraman**, and Vedant Khandelwal. "Process knowledge-infused ai: Toward user-level explainability, interpretability, and safety." IEEE Internet Computing 26, no. 5 (2022): 76-84.

+ Amit Sheth, Kaushik Roy, **Revathy Venkataramanan,** Venkatesh Nadimuthu. "C 3 AN: Custom, Compact and Composite AI Systems-A NeuroSymbolic Approach: 4 th-Generation Evolution of Intelligent Systems." (In print CACM2025).

+ Kim, Hyunwook, **Revathy Venkataramanan,** and Amit Sheth. "A Survey on Food Ingredient Substitutions." arXiv preprint arXiv:2501.01958 (2024). (Under Review, ACM Computing Healthcare)

AI Pipeline Recommendation

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Smart Manufacturing

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Open Source Contributions

AIMKG with Recommender

AI pipeline Metadata Knowledge Graph along with Neurosymbolic recommender has been open-sourced by HPE. Link: https://github.com/HewlettPackard/ai-metadata-knowledge-graph

Disease-specific Food Knowledge Graph

The Disease-specific Food Knowledge Graph constructed in the context of diabetes for USFDA ingredients has been open-sourced. (Working on GitHub Page)

Multimodal Ingredient Subsitution Knowlege Graph

To follow-up suitability analysis with ingredient subsitution recommendation, Multimodal Ingredient Subsitution Knowledge Graph was built with 80k substitution pairs and it is open-sourced. Link: https://github.com/kanak8278/MISKG/tree/main

Diabetes-specific Recipes

Benchmarking dataset with recipes suitable and not suitable for diabetes. (Working on GitHub Page)

Cooking Action Dataset

Cooking action extraction dataset and model, one of the least explored areas. Link: https://github.com/revathyramanan/cooking-action-generation

Ingredient Images to Recipe1M

Extending Recipe1M dataset with ingredient images crawled from Bing API. Link: https://drive.google.com/drive/folders/1Q7RQ-4FP7N44A9kIPhpBzf7ho0dfzt4H?usp=drive_link

Dynamic Process Ontology

DMPKG representation for smart manufacturing to provide user-level explanations for anomaly prediction and detection, a Dynamic Process Ontology was developed and deployed in real-time. Link: https://github.com/revathyramanan/Dynamic-Process-Ontology

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Patents

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Tutorials & Workshops

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02. Hong Yung Yip, Ruwan Wickramarachchi, **Revathy Venkataramanan**, and Amit Sheth, “Knowledge-driven Processes for Big Data Management and Applications,” tutorial at IEEE BigData Dec 2024.

03. Tarun Kumar, Deepak Maurya, **Revathy Venkataramanan**, Rucha Bhalachandra Joshi, “Graphs and more Complex structures for Learning and Reasoning”, workshop organization at the Association for the Advancement of Artificial Intelligence AAAI 2024.

AI Panels

AI in the workplace, AI Symposium, Greenville, SC.

Responsible use of AI, Aspire and Advance, Columbia, SC.

News Articles

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02. Edamam Provides Data for the Creation of an AI Model for Personalized Meal Recommendations, EIN PRESSWIRE. Link: https://www.einpresswire.com/article/744188562/edamam-provides-data-for-the-creation-of-an-ai-model-for-personalized-meal-recommendations

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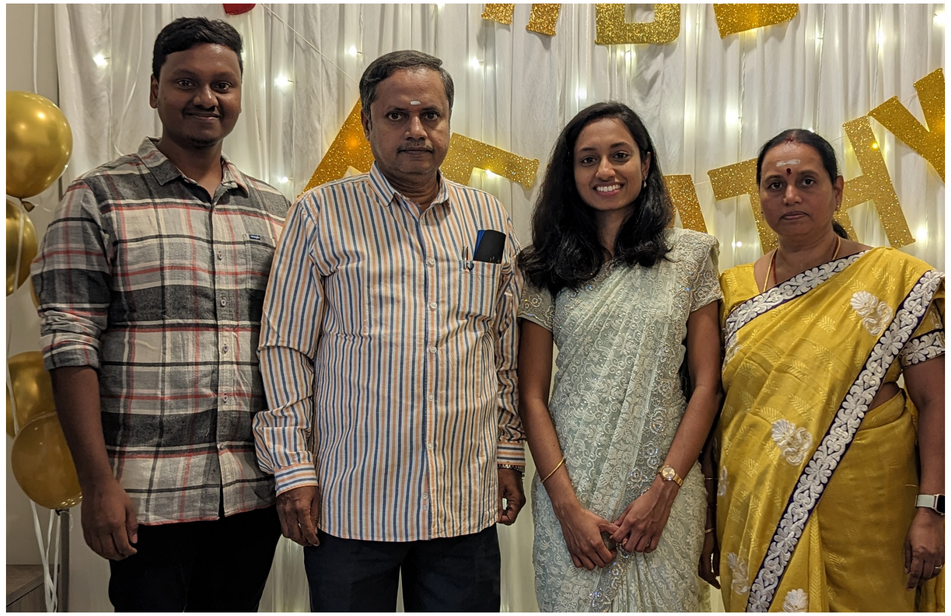

Thank you