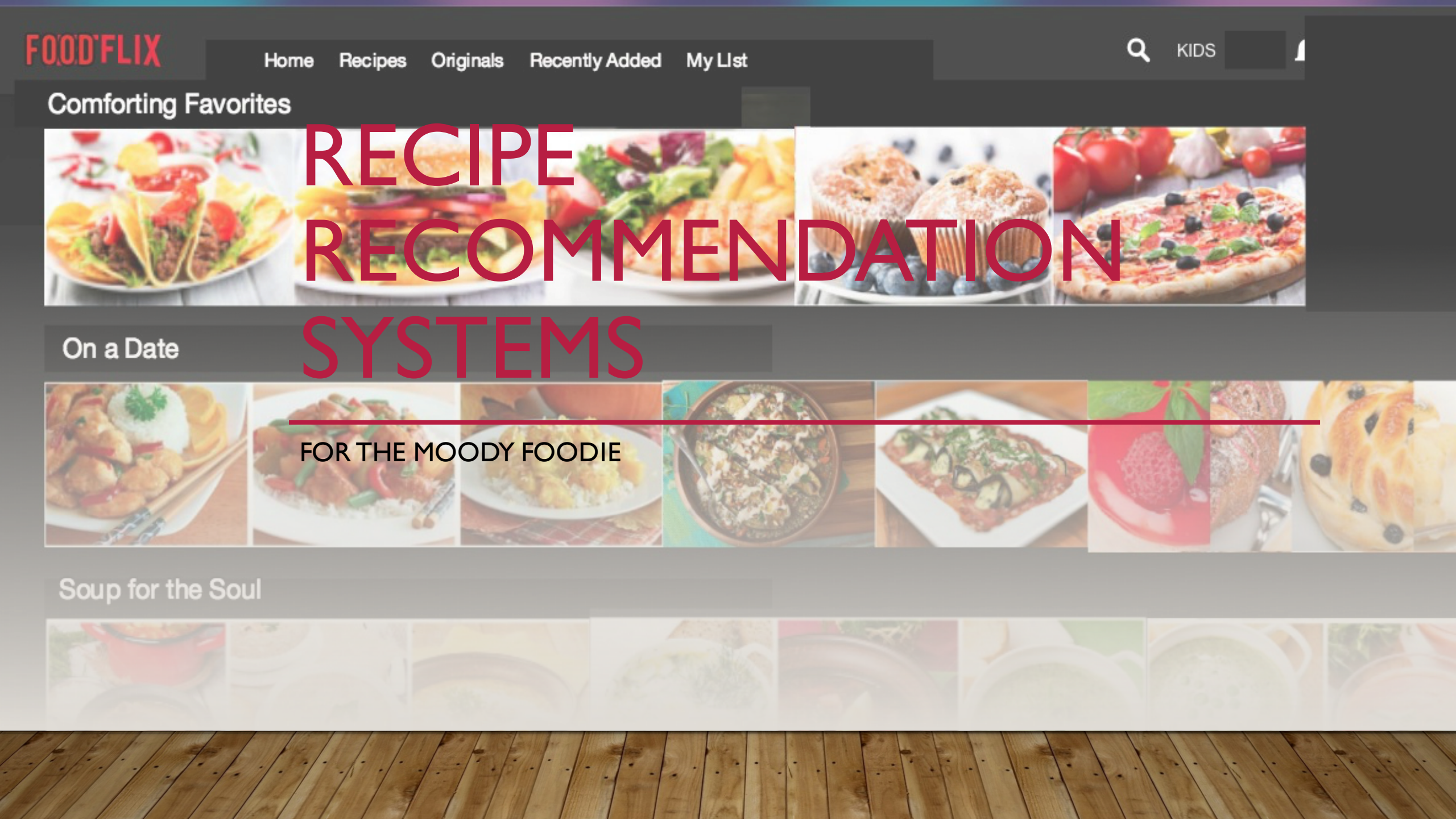
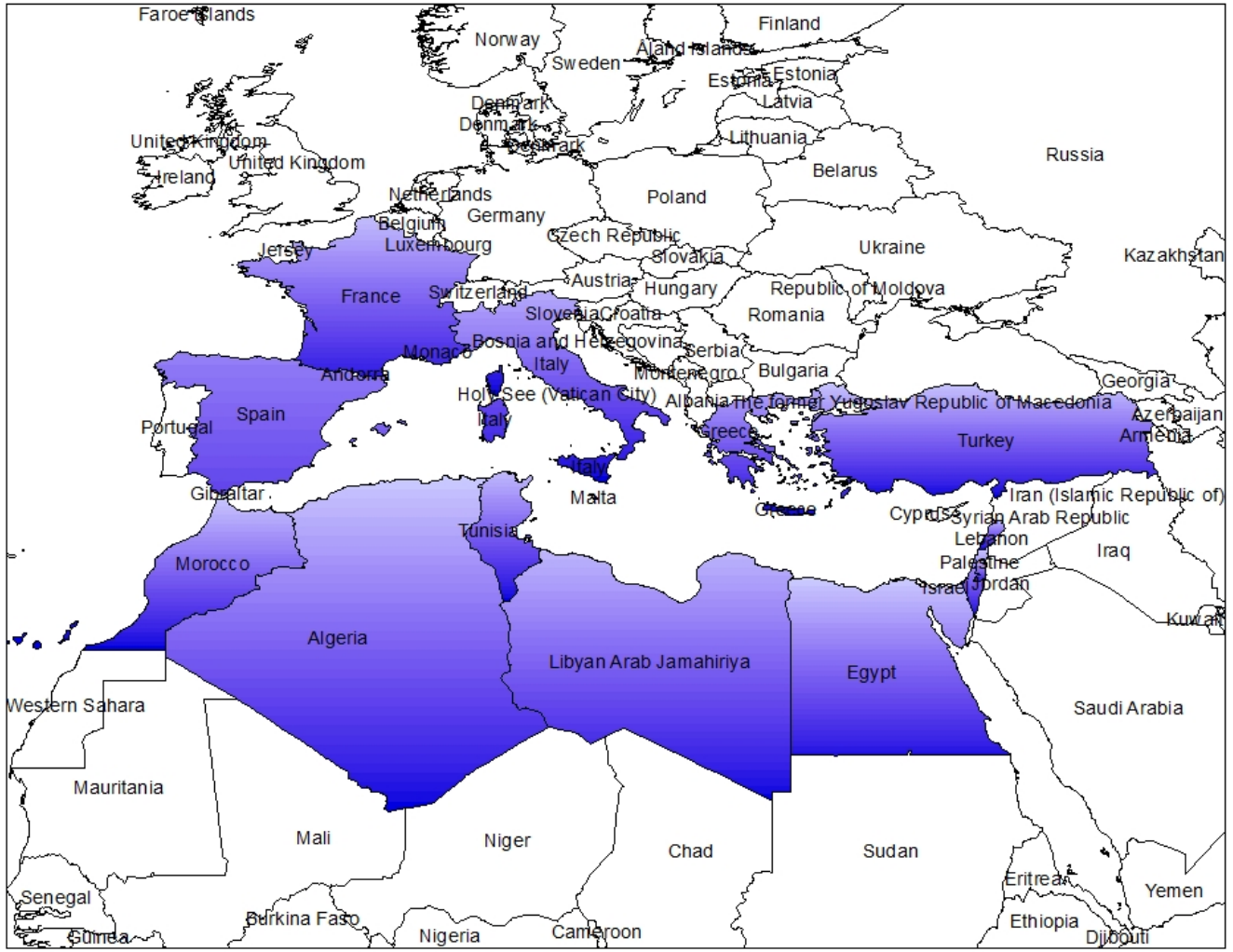


RECIPE RECOMMENDATION SYSTEMS

FOR THE MOODY FOODIE

WHAT IS MEDITERRANEAN FOOD?



SO, DISHES (/RECIPES)

SUPERCOOK

- You can't list your entire pantry
- You have to choose by self-filtering ingredients to those that match the first ingredient you listed. The website itself isn't doing that much.
- You aren't crawling the web. The recipe results are limited to Supercook's own recipes

MOTIVATING QUESTION: HOW DOES ONE IDENTIFY SALIENT FEATURES?

Content-Based

- Ingredients: Freyne and Berkovsky; Ghewari
- Ingredients+: Zhang et al.
- Image Classification

Collaborative Filtering

- Popularity data among users

User-Centered Approach

- User preferences

User-Centered and Structural Approach

- Wang et. al

HOW TO ASSESS

Content-based approach

INGREDIENTS

- Ingredients are good at predicting your geographic location or origins, rather than the similarity of one dish to another (Ghewari et al. (78%))

Three levels of importance for ingredients

- Issue: Manual assignment of levels. Researchers decide what is considered an "important" ingredient.
- More important ingredients contribute more to similarity score
- Rare ingredients also important (Kim et al.)

HOW TO ASSESS

User-Centered + Structural approach

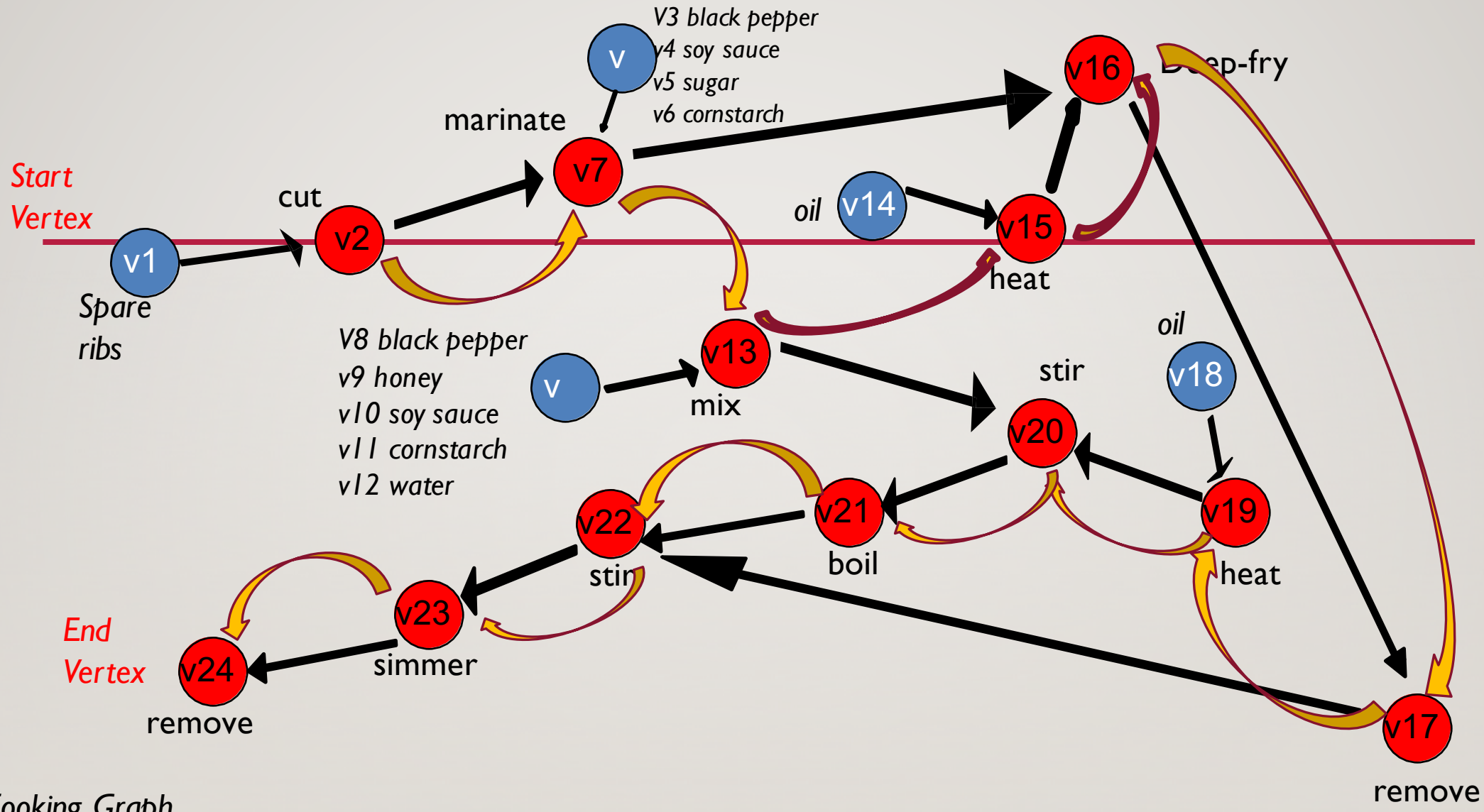
RECIPEVIEW

$$sim(SP_1, SP_2) = \left[\left(\sum_{i=1}^{m} |E_{Si}| \left(\mu |E_{SAi}| + \gamma |E_{SIi}| \right) \cdot \log_2 \frac{N}{d_{Si}} \right) \cdot Per(SP_1, SP_2) \right]^{1/2} \quad (1)$$

where $|E_{Si}|$ is the number of edges (including both action and ingredient edges) of the subgraph SP_{Si}; $|E_{SAi}|$ and $|E_{SIi}|$ are the numbers of action and ingredient edges in SP_{Si} respectively (i.e. $|E_{Si}| = |E_{SAi}| + |E_{SIi}|$); N is the total number of recipes; d_{Si} is the number of cooking graphs that contain subgraph SP_{Si}; $\log_2(N/d_{Si})$ is the inverse subgraph frequency, the purpose of which is to make rare common subgraphs more important than frequent ones.

- Convert recipes into cooking graphs: Recipe structures = cooking patterns
- Similarity (using FSG algorithm) seen as ingredients, actions and cooking patterns of ingredient/actions flows: Local AND Global

- Searchable by difficulty (length of graph), with cook time as a proxy, or by calories
- Structure comparison may also account for difficulty level factor
- Shouldn't sort by 100% similarity, because it's likely you'd get Kung Pao Chicken with Kung Pao Pork



Cooking Graph

Action

Raw Ingredients

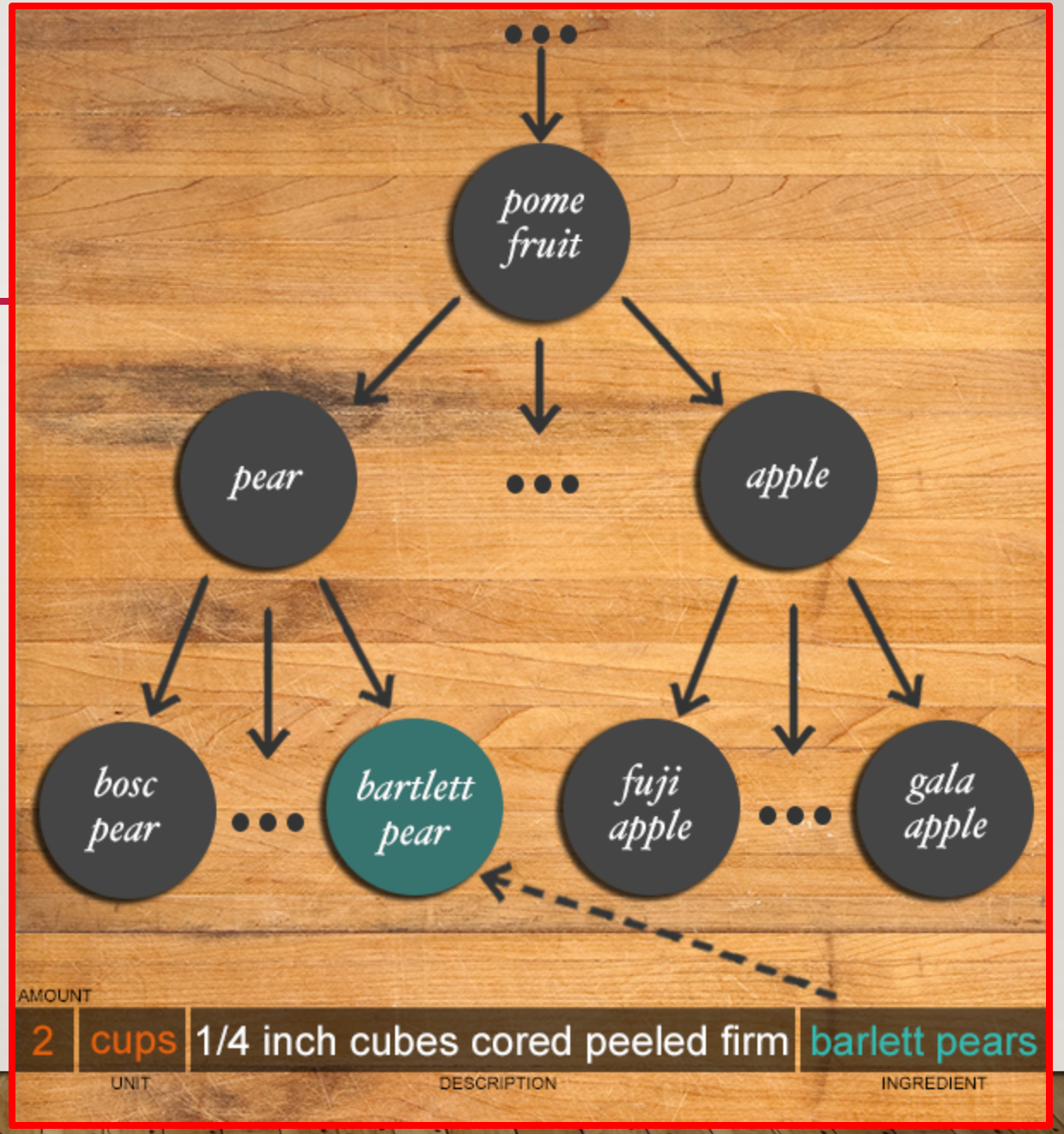
Ingredients Flow

Action Flow

Cooking Graph of 'Hu Die Gu'(Chinese)

YUMMLY

- Relationships between ingredients
- Factors that come with recipe: calories, flavor (sweet, spicy, mild), course (breakfast, lunch, snack), preparation time,
- Learned factors: Cuisine and relevant occasions (what is Super Bowl food?)
- User searches (food trends, time sensitive searches)



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….Mood?

HOW DOES MOOD AFFECT FOOD CHOICE?

	Comfort food	Rainy weather	Fancy food
American			 
Indian		 	

- Folksonomy: collaborative tagging (Yu)
- Categorical model and dimensional model – present same issue as other recommender system subjects

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