





# Flavor network and the principles of food pairing

SUBJECT AREAS:

STATISTICAL PHYSICS, THERMODYNAMICS AND NONLINEAR DYNAMICS

**APPLIED PHYSICS** 

SYSTEMS BIOLOGY

**STATISTICS** 

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STATISTICS

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## Introduction

- Are there any general patterns that determine the ingredient combinations used in food today or principles that transcend individual tastes and recipes?
- A flavor network that captures the flavor compounds shared by culinary ingredients
- Food Paring Hypothesis: "Ingredients sharing flavor compounds are more likely to taste well together than ingredients that do not"
- A systematic understanding of culinary practice.
  - Number of recipes (cookpad): 10<sup>6</sup>
  - Number of potential recipes:  $> 10^{30}$
  - Number of recipes used for the studies: 56498

# Summary

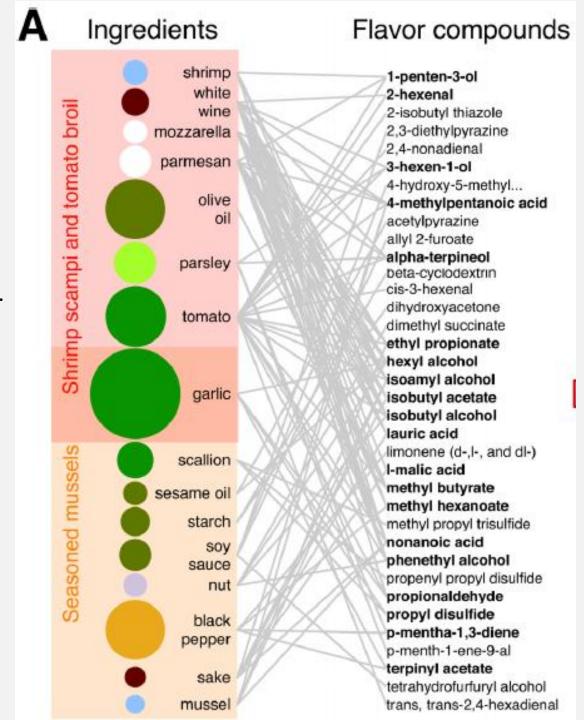
- The flavor network allows us to reformulate the food pairing hypothesis as a topological property: Do we more frequently use ingredient pairs that are strongly linked in the flavor network or do we avoid them?
- To test this hypothesis we need data on ingredient combinations preferred by humans, information readily available in the current body of recipes.
- For generality, 56,498 recipes, provided by two American repositories (epicurious.com and allrecipes.com), were used.
- To avoid a distinctly Western interpretation of the world's cuisine, we also used a Korean repository (menupan.com).
- The recipes are grouped into geographically distinct cuisines (North American, Western European, Southern European, Latin American, and East Asian).

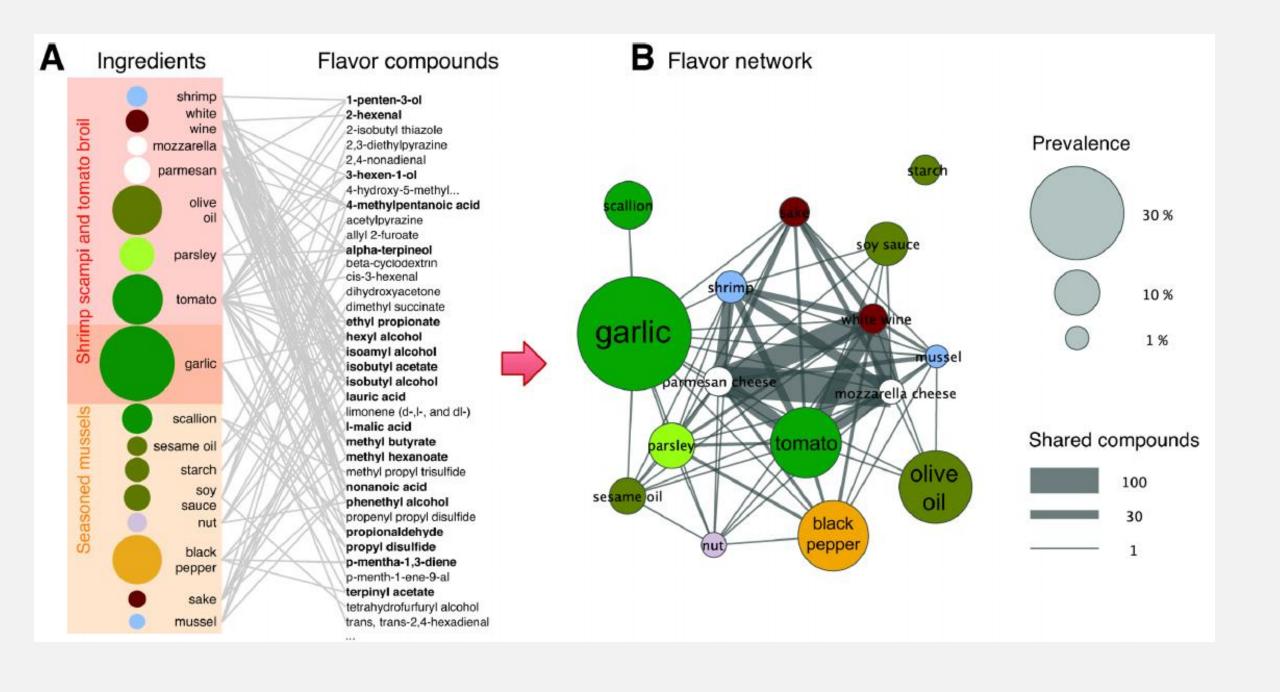
#### **Basis of Flavor Network:**

- (i) 381 ingredients used in recipes throughout the world, and
- (ii) 1,021 flavor compounds that are known to contribute to the flavor of each of these ingredients.

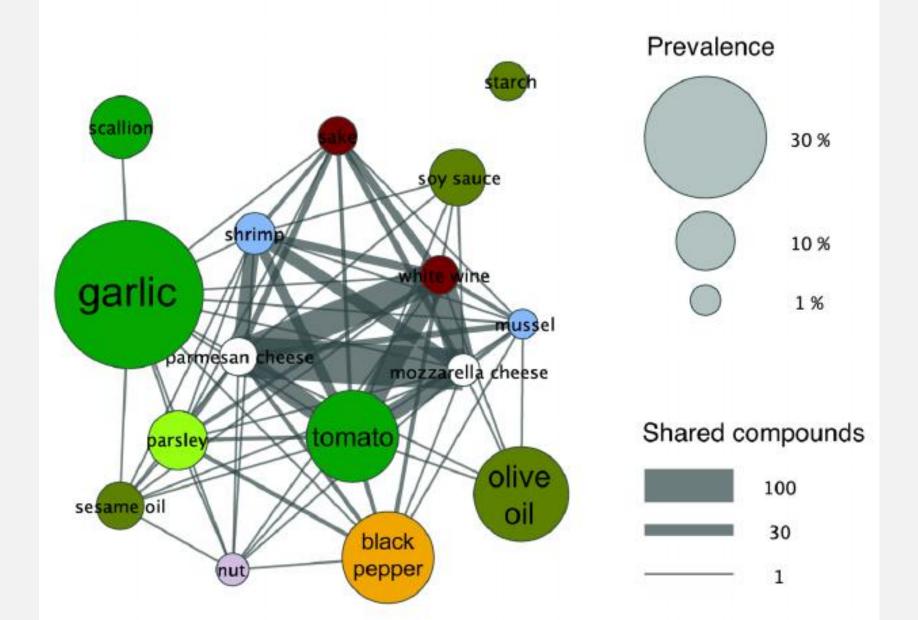
$$< k > = 214$$

www.epicurious.com www.allrecipes.com

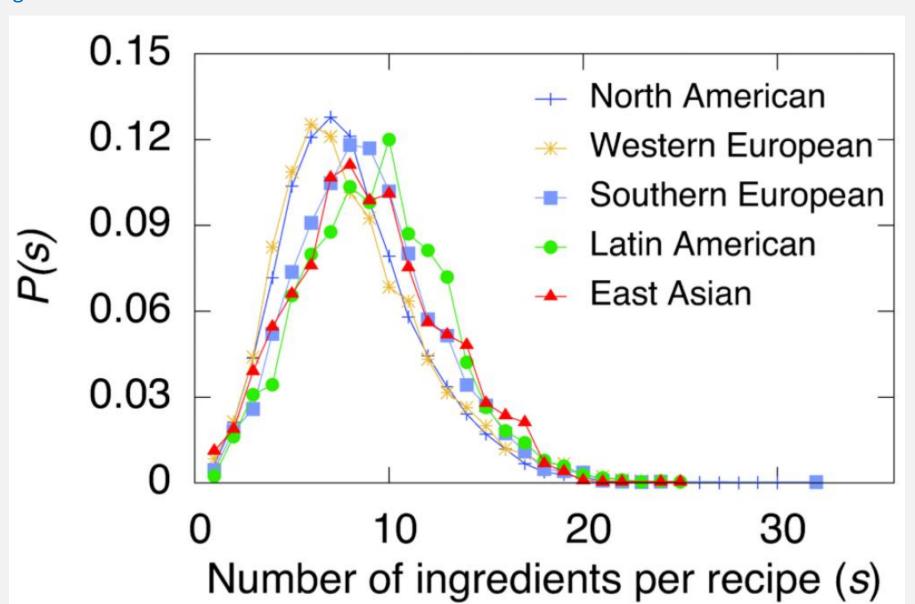




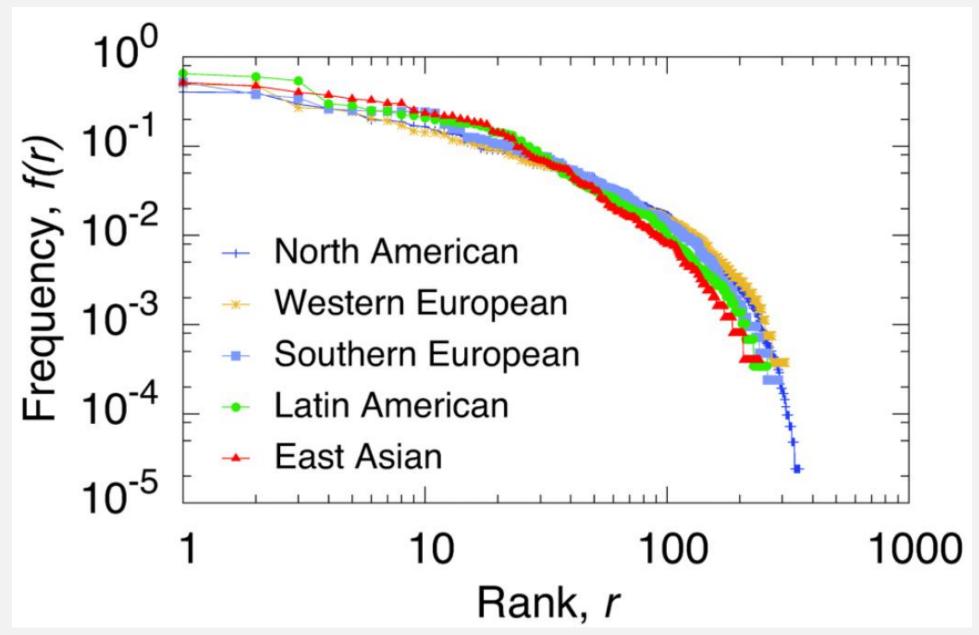
## **B** Flavor network

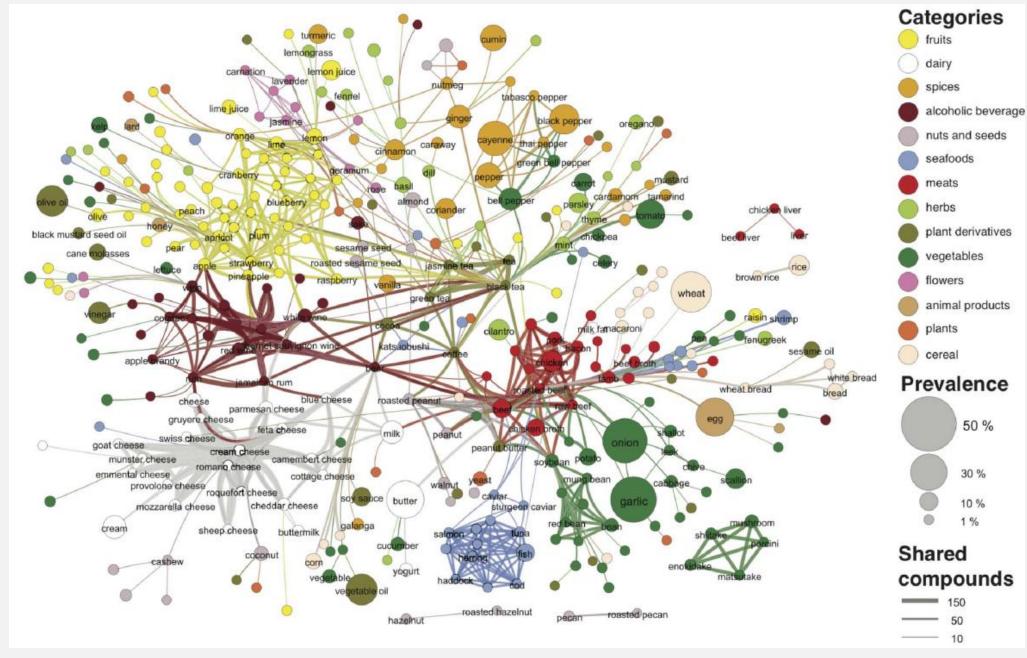


The average number of ingredients used in a recipe is around eight, and the overall distribution is bounded, indicating that recipes with a very large or very small number of ingredients are rare.

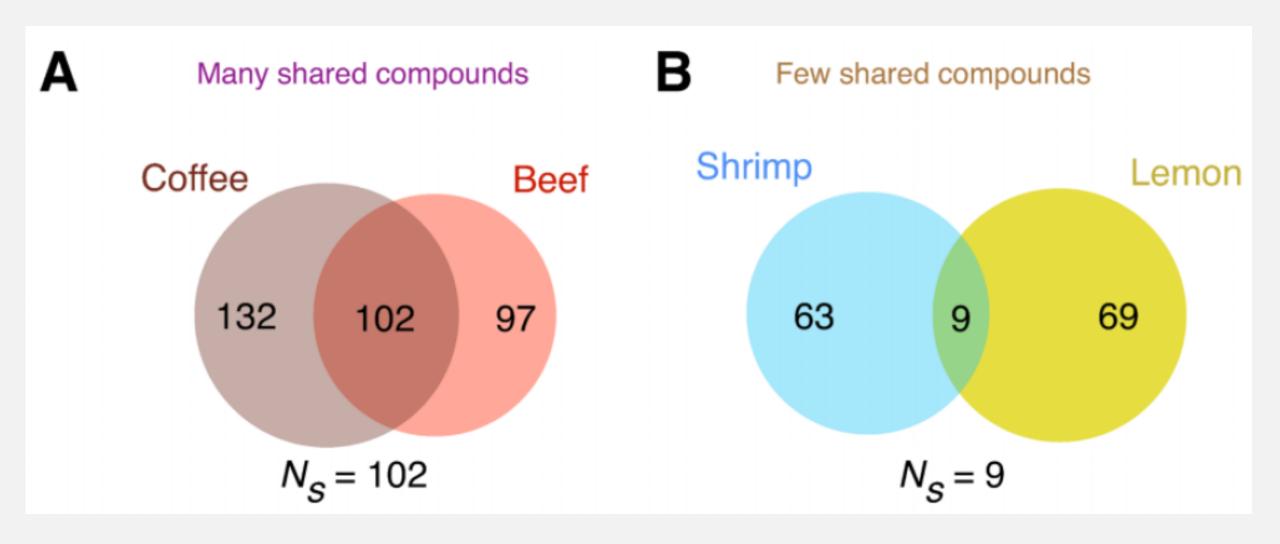


Ingredients Jasmine tea, Jamaican rum, and 14 other ingredients are used only in one recipe.



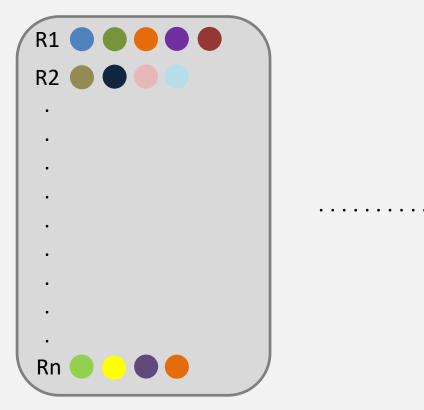


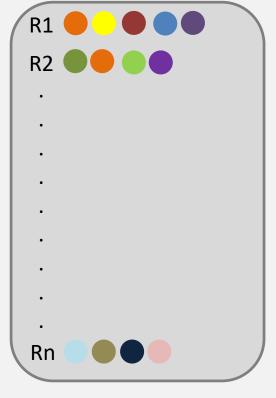
Backbone extraction algorithm



### How to create a random cuisine? (Strategy -1)

- (1) Corresponding to every recipe, create its size-controlled randomized version by randomly sampling ingredients from the 'Ingredients Basket' (without replacement).
- (2) Having thus created 'a randomized cuisine', create a large number of such cuisines (say, 100) for statistical analysis.



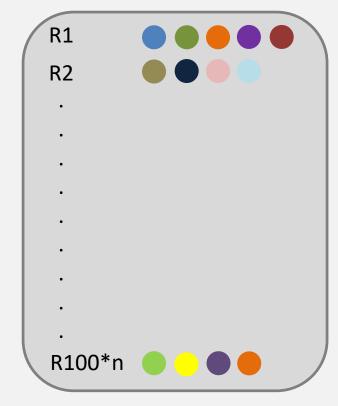


Randomize cuisine 1

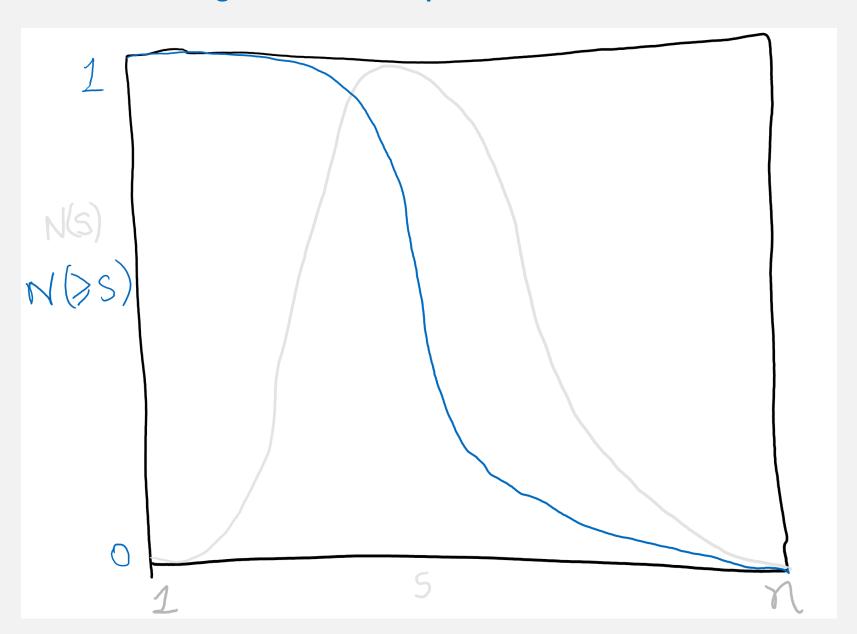
Randomize cuisine 100

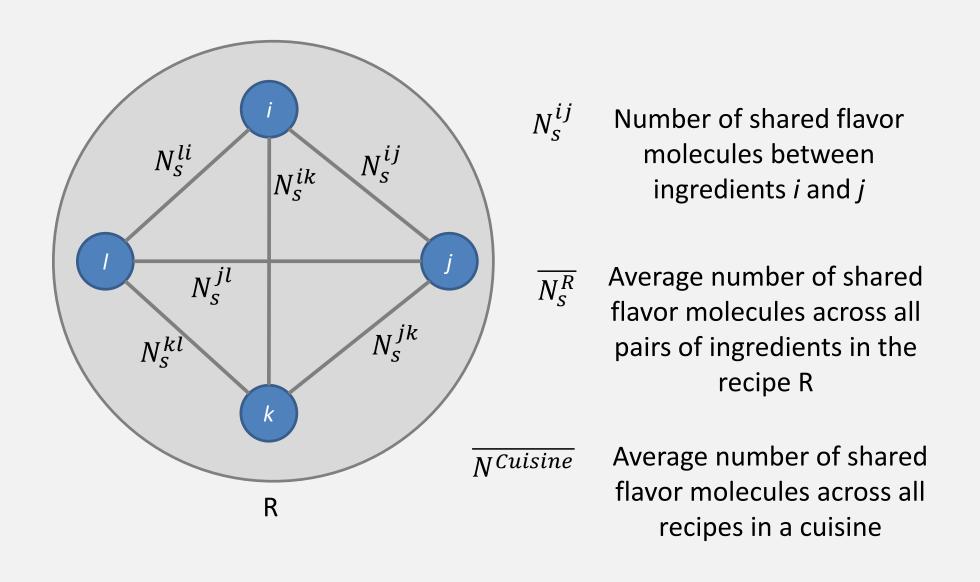
#### How to create a random cuisine? (Strategy − 2)

- (1) Find the 'recipe size distribution' of the cuisine.
- (2) Find the 'cumulative recipe size distribution' of the cuisine.
- (3) Generate a random number to pick a recipe size.
- (4) Create the recipe by randomly sampling ingredients from the 'Ingredients Basket' (without replacement).
- (5) Generate a large number of recipes (say, 100 times the total number of recipes) for statistical analysis.



## Generating the desired recipe size distribution of the cuisine





## Ideas

- A theoretical model for food pairing.
- Starting with a 'basket of ingredients and their flavor profile, implement strategies for 'pairing' and observe the cuisine architecture.
- Create a python library for the analysis of cuisine, starting with cuisine data imported in a certain format.
- Recipe size distribution, ingredient popularity stats
- Category composition analysis
- Itemset analysis
- Food pairing analysis
- Random cuisine generation

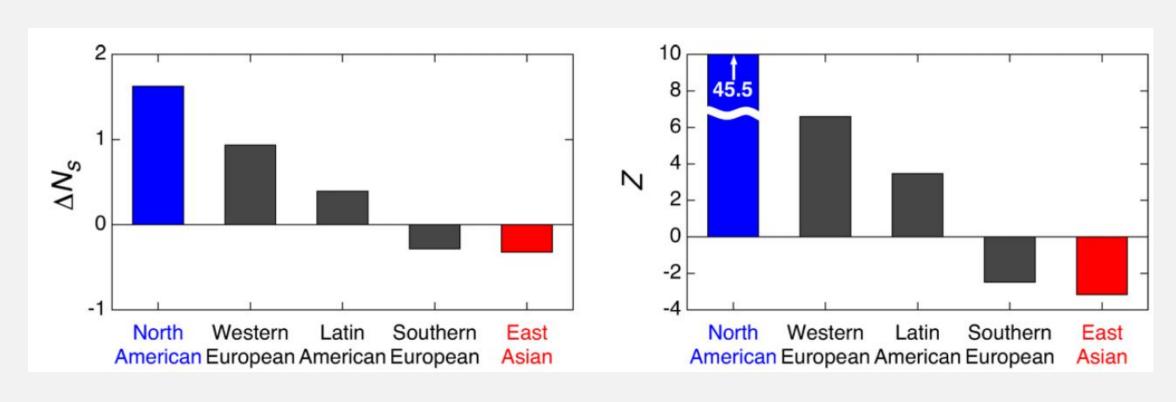
## - Create Computational Gastronomy Kaggle challenges

- For a given set of recipes, predict their cuisine.
- Given the flavor profile of an (unlabeled) ingredient, predict its cuisine.
- Given a molecule (SMILE format), predict its taste (bitter, sweet, tasteless).
- and more.

#### Random Cuisine and comparison of food pairing

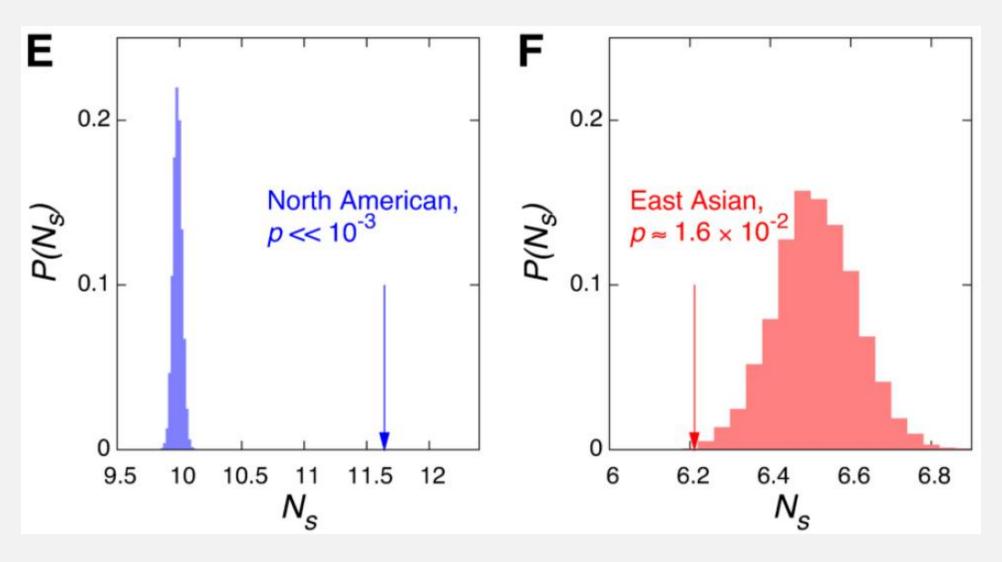
North American and Western European cuisines exhibit a statistically significant tendency towards recipes whose ingredients share flavor compounds.

By contrast, East Asian and Southern European cuisines avoid recipes whose ingredients share flavor compounds.

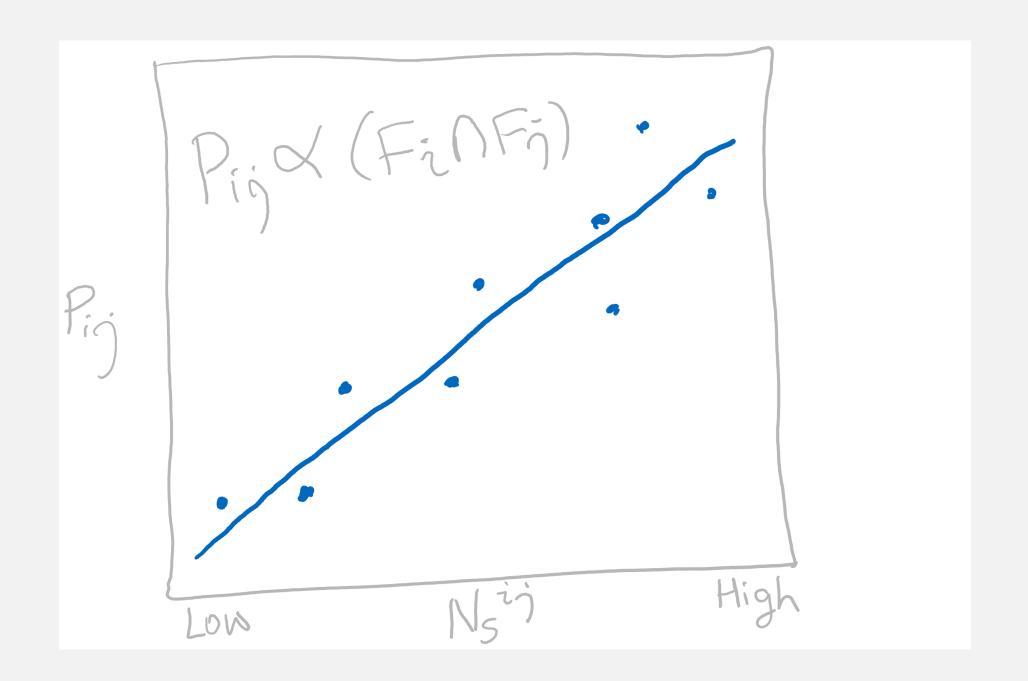


Z = Touisine Touisine-Rand Grand Navisine Ns ausme-Rand

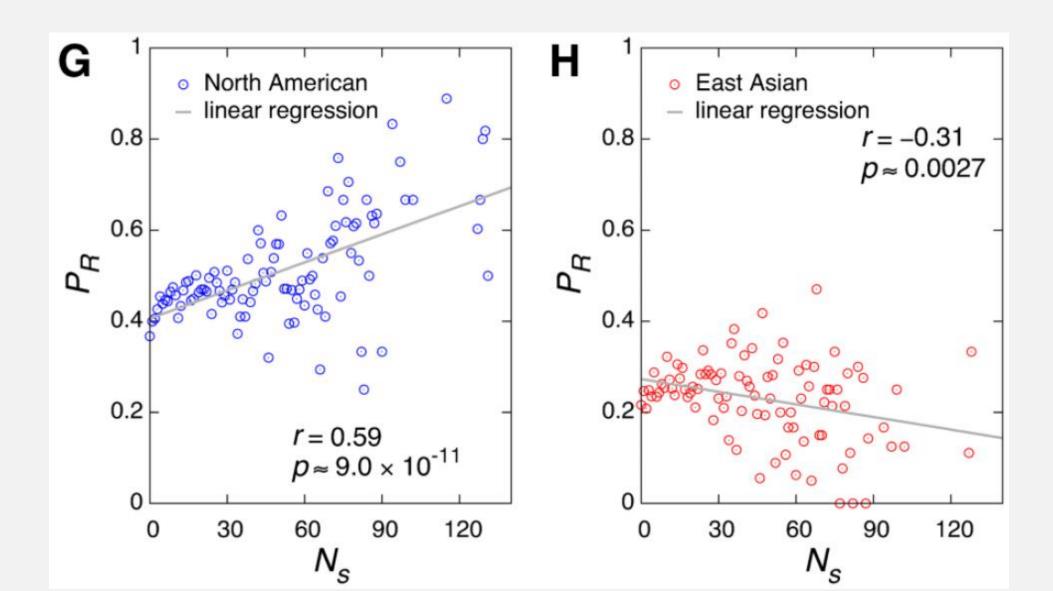
### **Distribution of Ns**



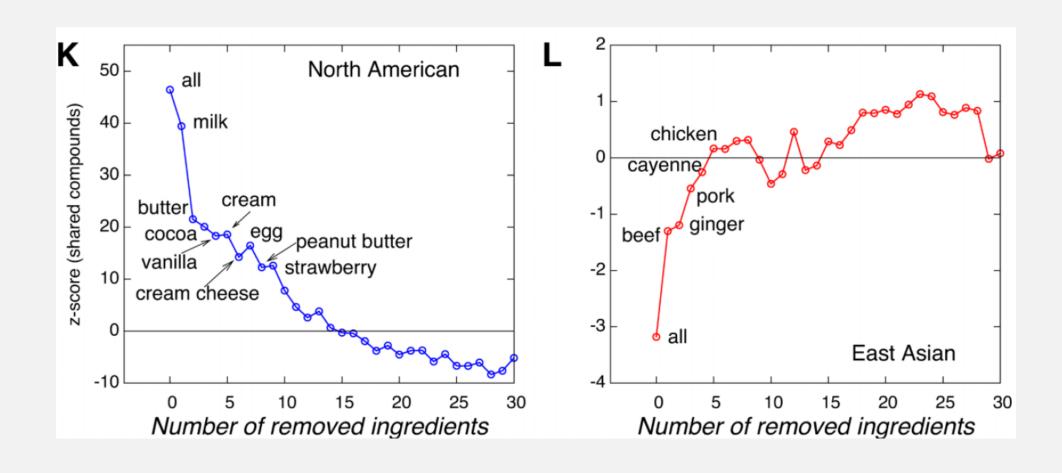
Ns: observed number of shared compounds characterizing the cuisines.

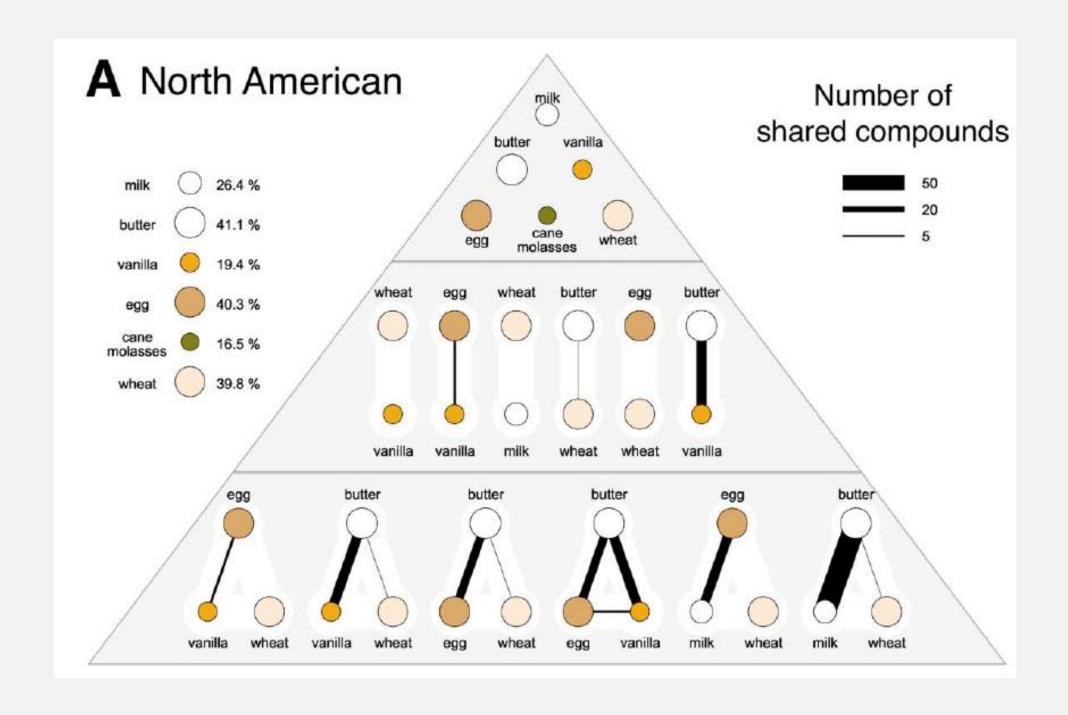


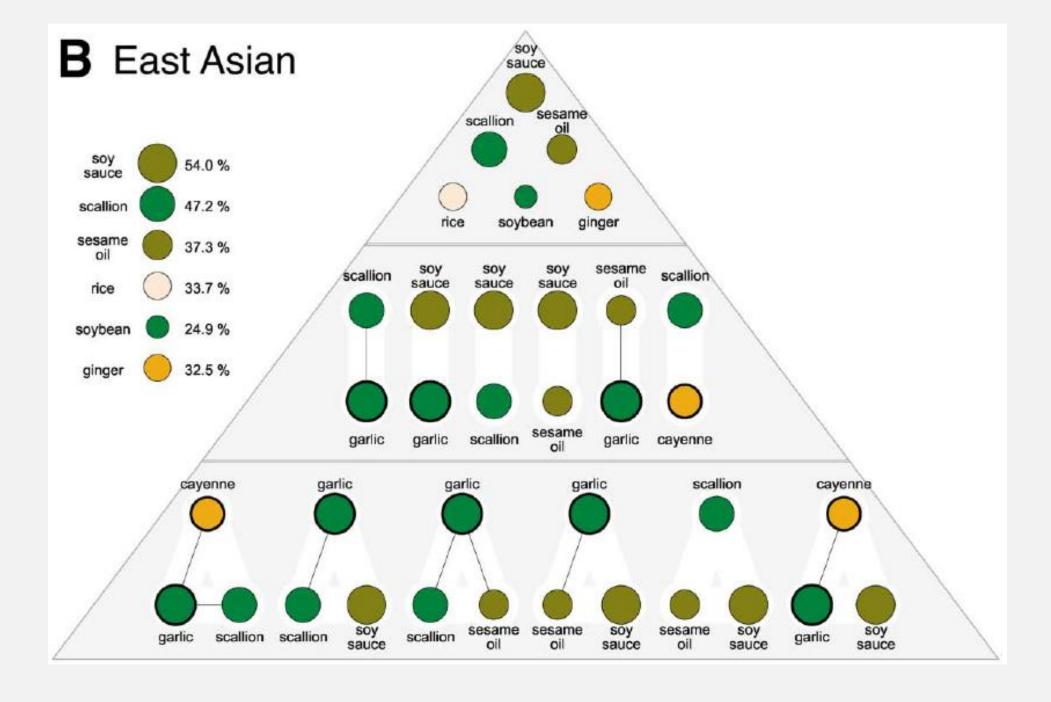
East Asian (Korean) cuisine the more flavor compounds two ingredients share, the less likely they are used together.



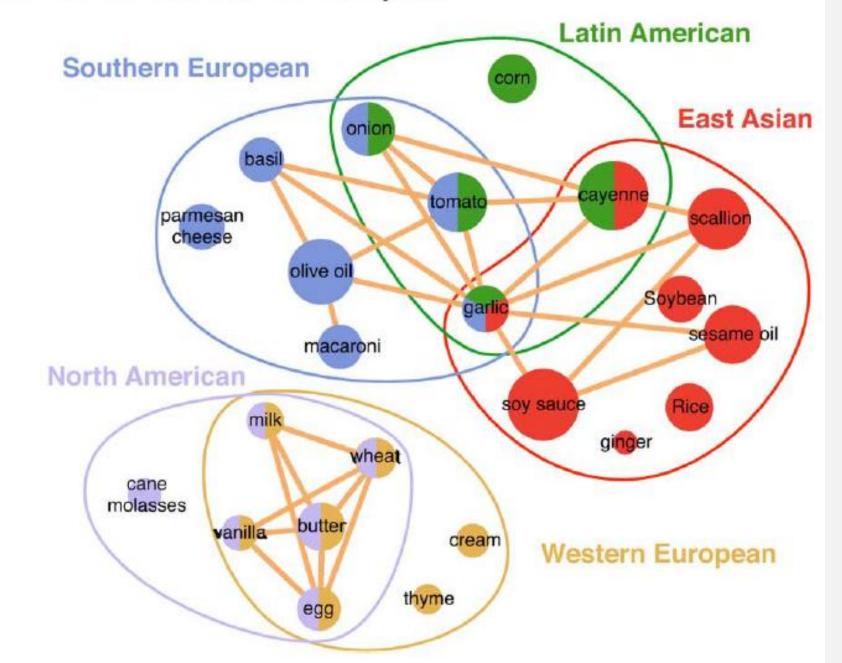
### Contribution of individual ingredients towards the observed food pairing phenomena





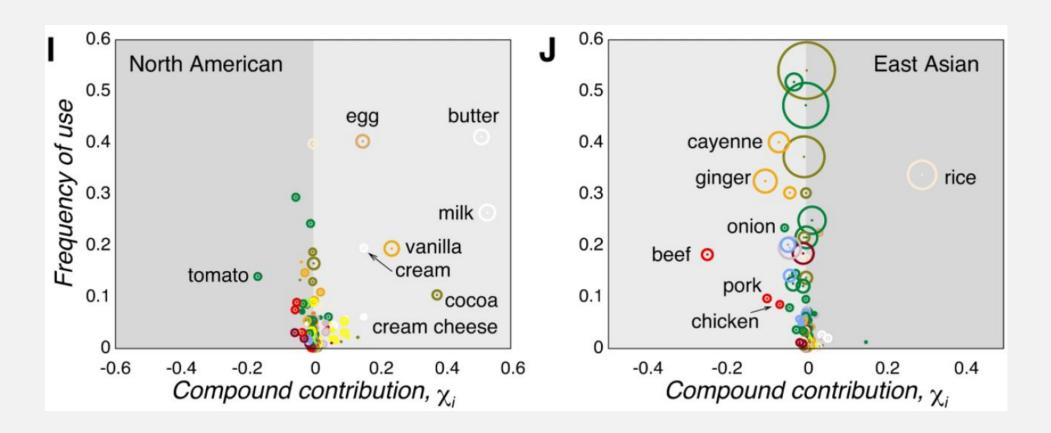


# C Co-occurrence in recipes



- Western Cuisines use ingredient pairs that share many flavor compounds
- By contrast, Korean cuisine tend to avoid compound sharing ingredients.

## Contribution of an ingredient towards the food pairing pattern



$$\chi_i \left( \frac{1}{N_c} \sum_{R \ni i} \frac{2}{n_R(n_R - 1)} \sum_{j \neq i(j, i \in R)} |C_i \cap C_j| \right) - \left( \frac{2f_i}{N_c \langle n_R \rangle} \frac{\sum_{j \in c} f_j |C_i \cap C_j|}{\sum_{j \in c} f_j} \right)$$