The Flavour Network

Science Makers

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Molecular Gastronomy

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An area which has received some attention as well are the **chemical compounds** that give food its **flavour**.

Food pairings

In recent years it has been suggested by several chefs and food scientists involved in Molecular Gastronomy, that **two foods taste good together if they share chemical flavour compounds.**[1,2]

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2)http://www.foodpairing.be and http://blog.khymos.org

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In recent years it has been suggested by several chefs and food scientists involved in Molecular Gastronomy, that **two foods taste good together if they share chemical flavour compounds.**[1,2]

This allows for the **prediction** of surprising taste combinations.

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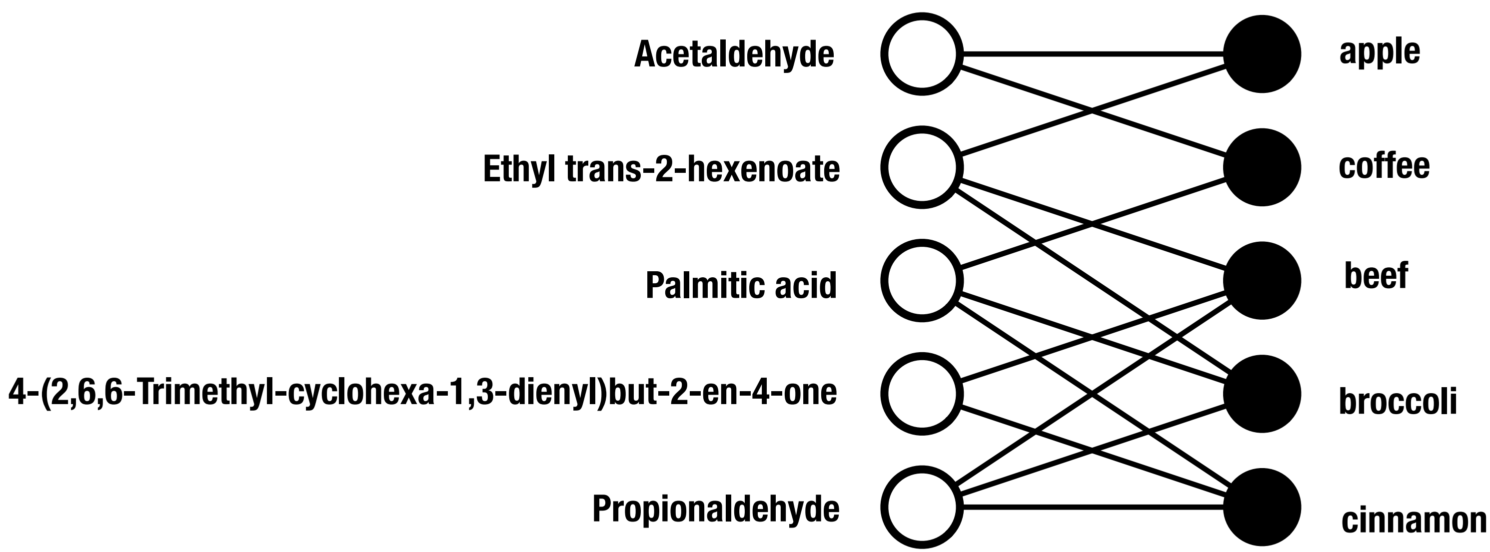
Bipartite network

Hence we can draw a so-called **bipartite network.**



Bipartite network

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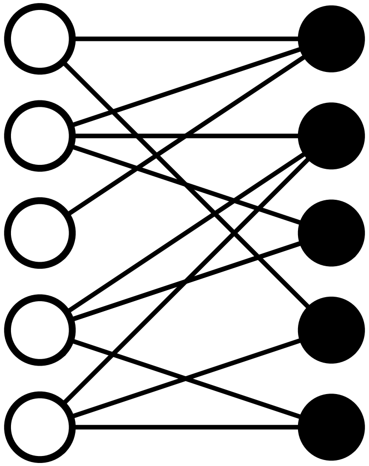
This is a field that has grown very rapidly over the last decade, after it was shown that **many different real-world networks share common features** and can be analysed using the same tools.

Bipartite network

Bipartite networks are common in everyday life and have been studied in great detail by network scientists.



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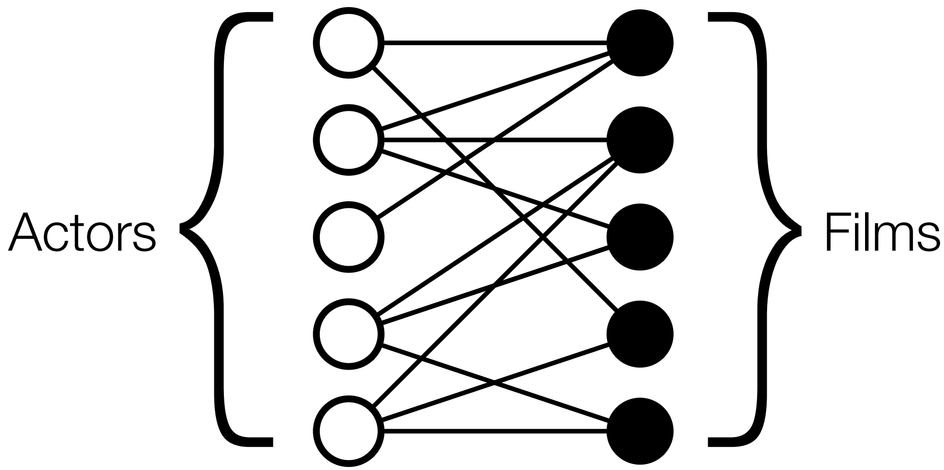

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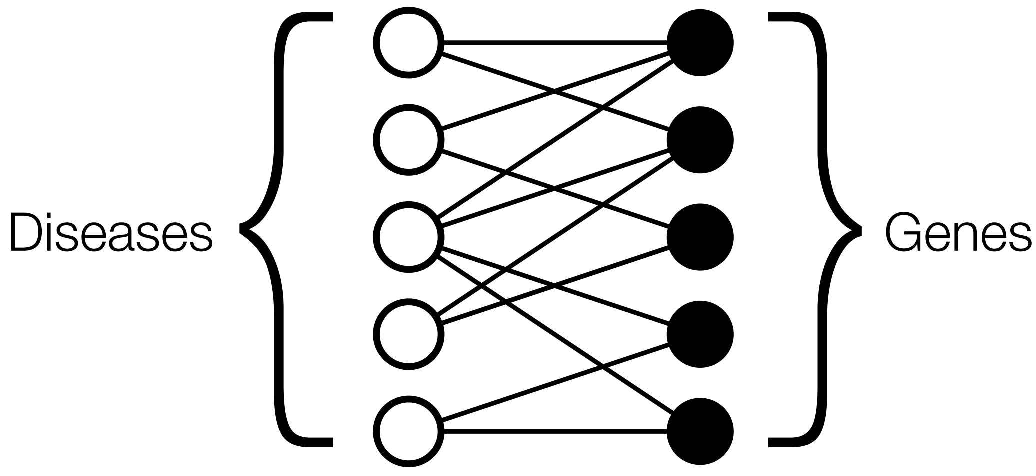

The data

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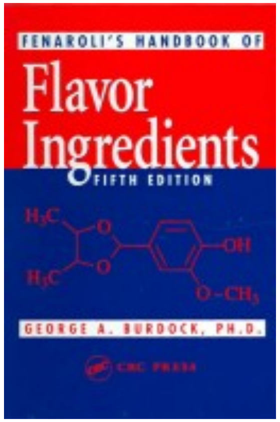
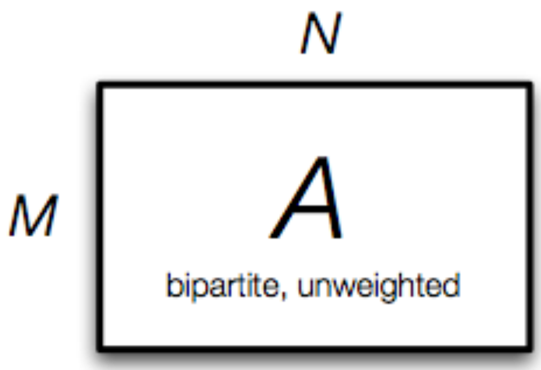
It was compiled from a reference handbook for food chemists [1], by looking up the natural occurrences of flavour compounds.



[1] G. A. Burdock, G. Fenaroli, *Fenaroli's Handbook of flavour Ingredients* (5th ed., CRC Press).

Bipartite network

The unweighted, bipartite adjacency matrix *A*,
of *M* **foods** and *N* **compounds**



One-mode projection

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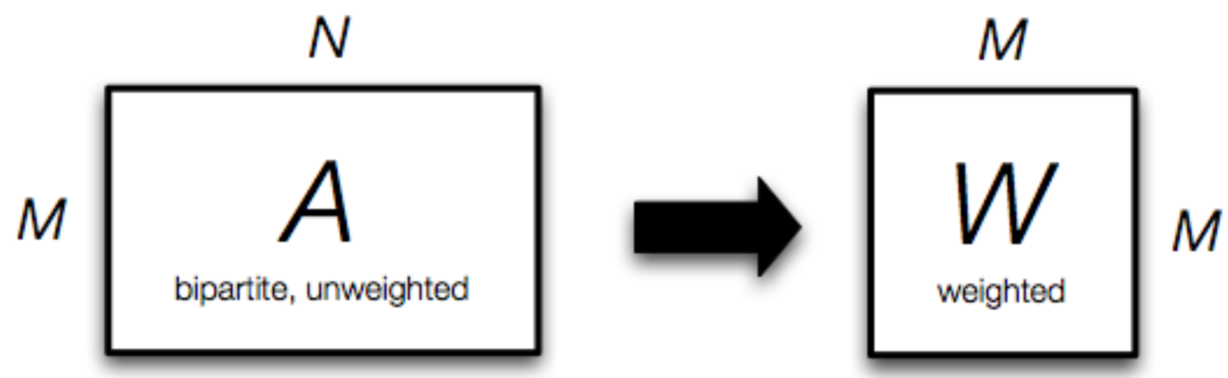


can be converted into a weighted *M* x *M* adjacency matrix *W*
of **foods** only, through a one-mode projection.

The weights

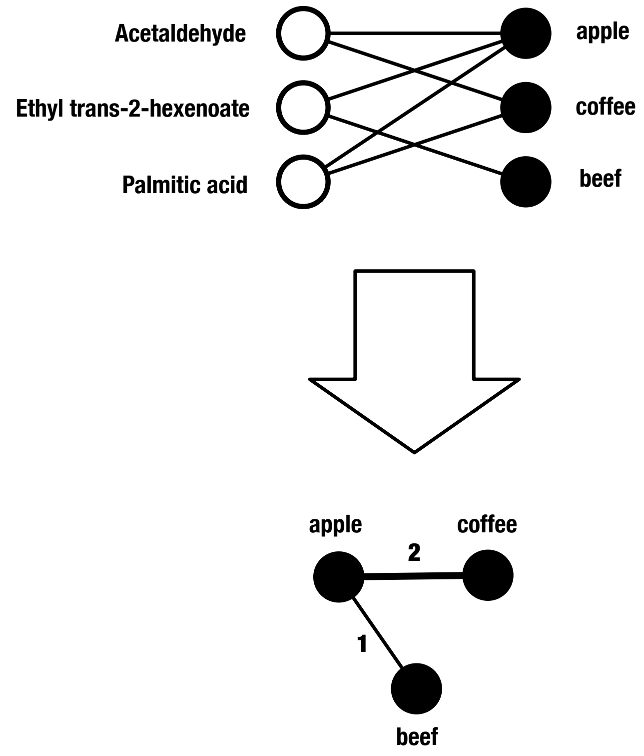
This means that the entries w_{ij} of the matrix *W,* given by

$$w_{ij} = \sum_{k=0}^{N} a_{ik} a_{jk}$$

indicate the number of **compounds** shared between **foods** *i* and *j*.

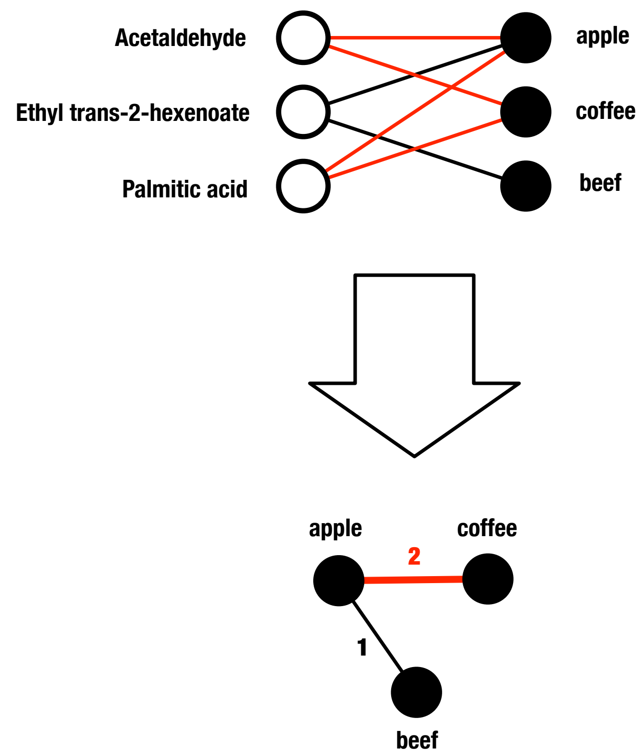
The weights

To give a simple illustration:



The weights

We see that **apple** and **coffee** share two compounds here.



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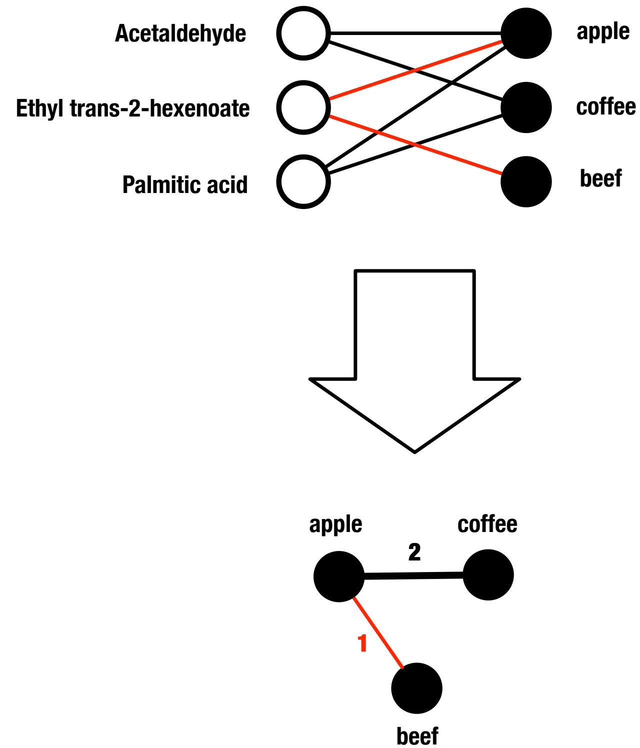
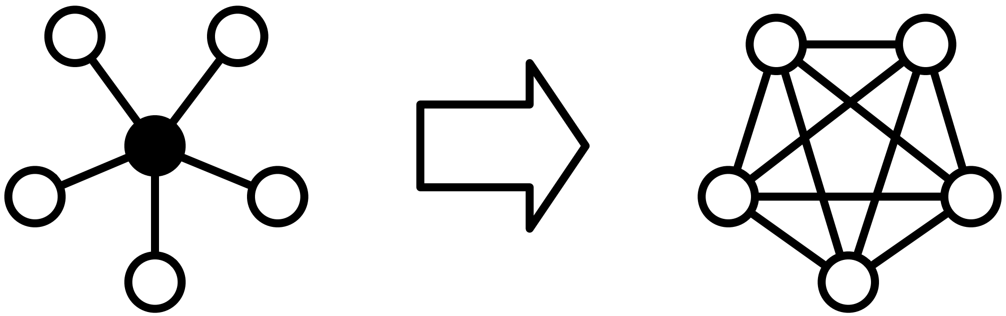


And **apple** and **beef** share one compound.

Too dense!

The resulting network between foods is **too dense** to be drawn in a meaningful way, because several compounds are shared by a large number of foods, which then become a fully connected subgraph.



Backbone extraction

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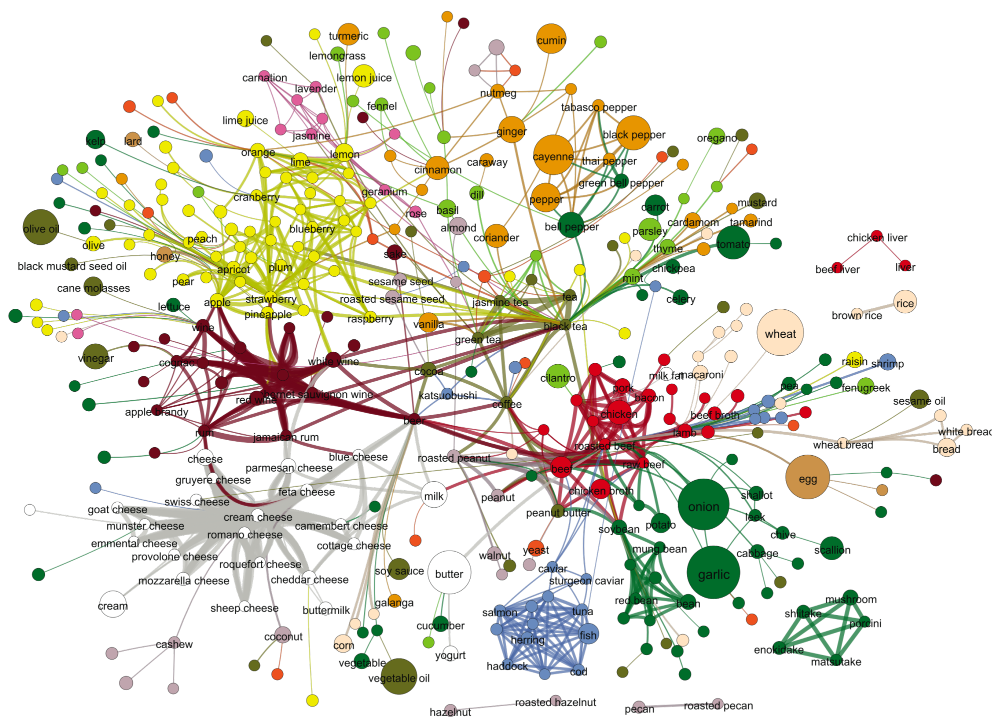
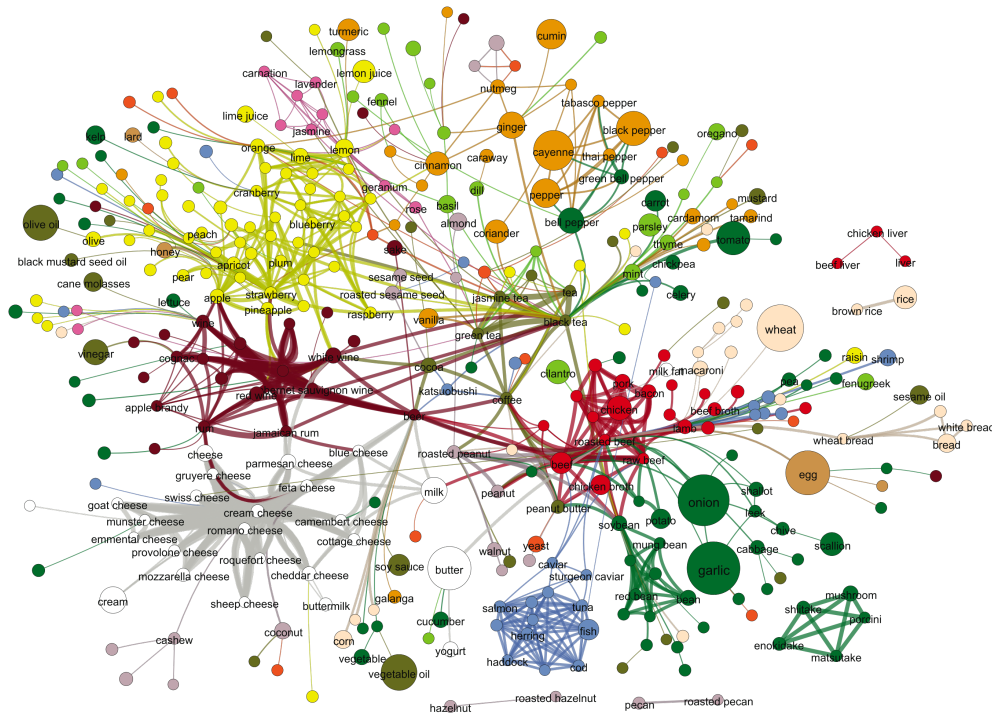
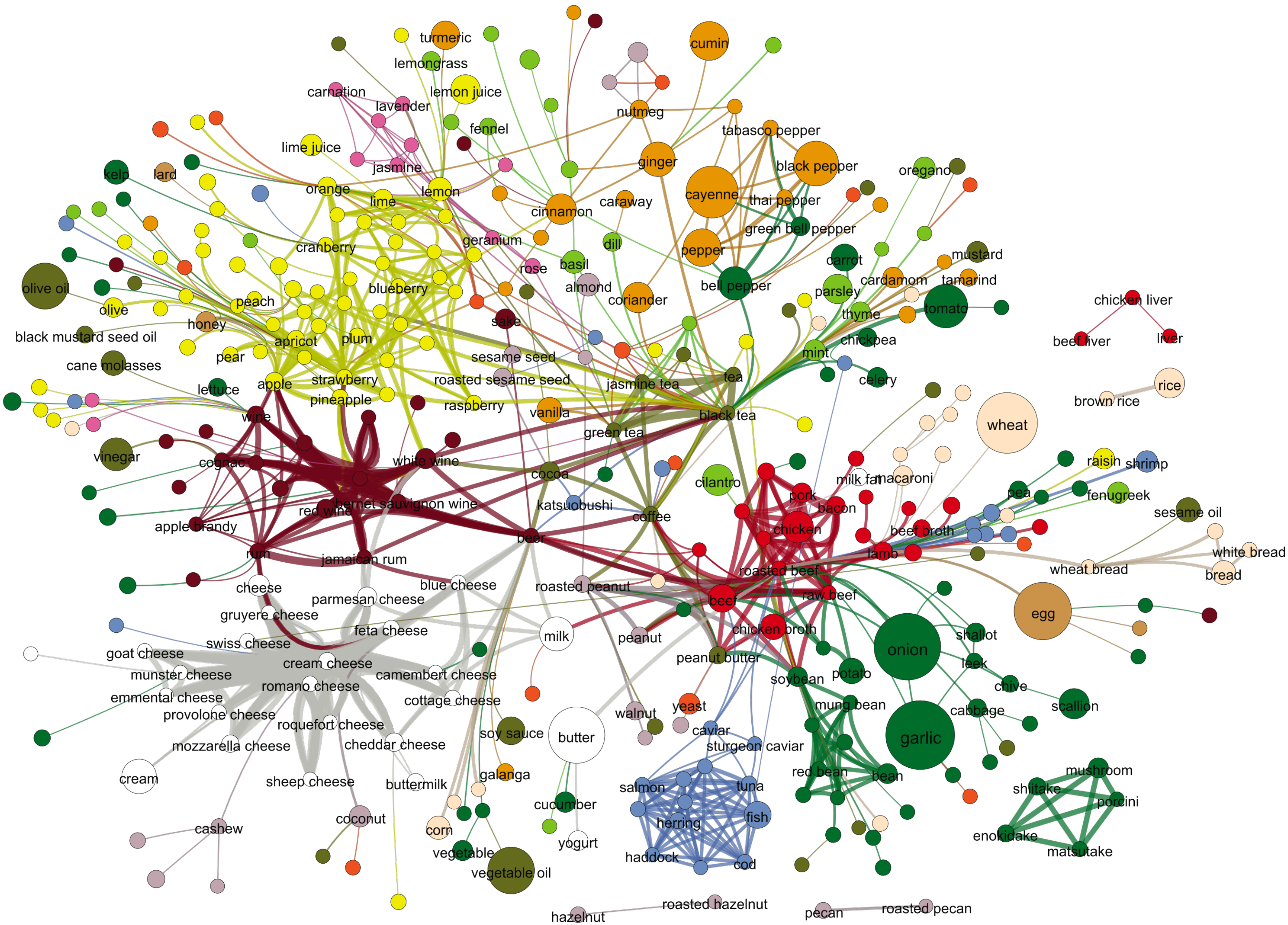


Backbone extraction

In order to visualize the network we extract its **backbone**, using the approach of Serrano et al. (PNAS, 2009).

We see a clear **modular** structure, which strongly correlates with the **food types** (colours), such as meat, fruit, vegetable, etc.





published in Y.-Y. Ahn, S. E. Ahnert, J. P. Bagrow, A.-L. Barabasi, Scientific Reports 1, 196 (2011)

Testing the hypothesis

Let us return to the beginning - the **hypothesis** was that two foods go together if they share compounds, and based on anecdotal evidence it seems to work.

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But can we test this **quantitatively**?

Recipes

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Yong-Yeol Ahn crawled **56498 recipes** from the

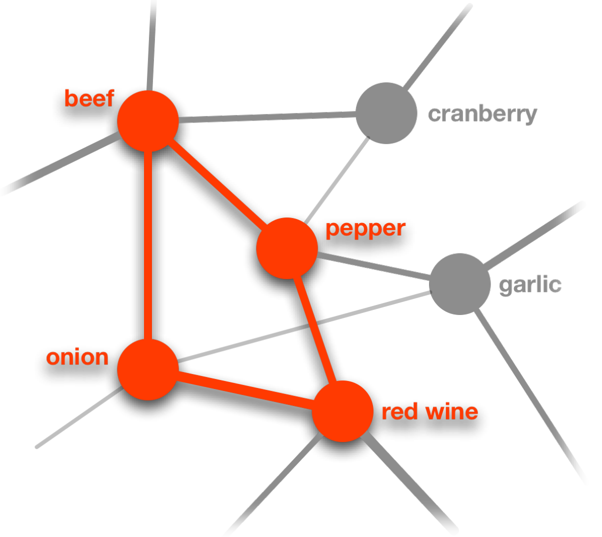
databases.

Recipes

A recipe *R* is a set of ingredients, and therefore corresponds to a **subgraph** in the flavour network.

To measure whether this recipe confirms the shared compound hypothesis, we can calculate the **average edge weight** in this subgraph:

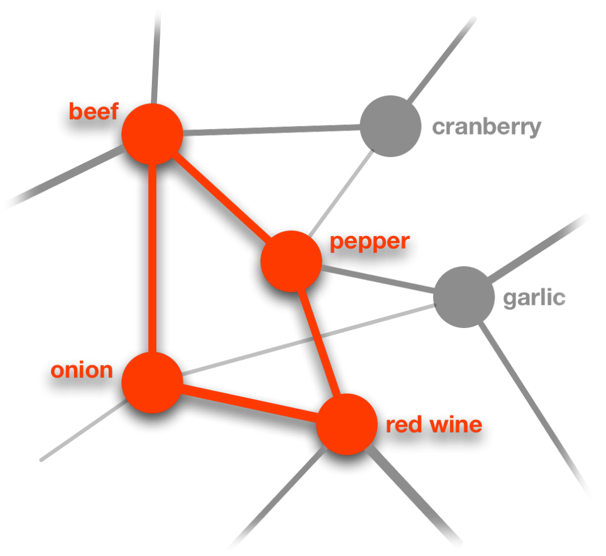
$$N_s(R) = \frac{2}{n(n-1)} \sum_{i,j \in R} w_{ij}$$



Recipes

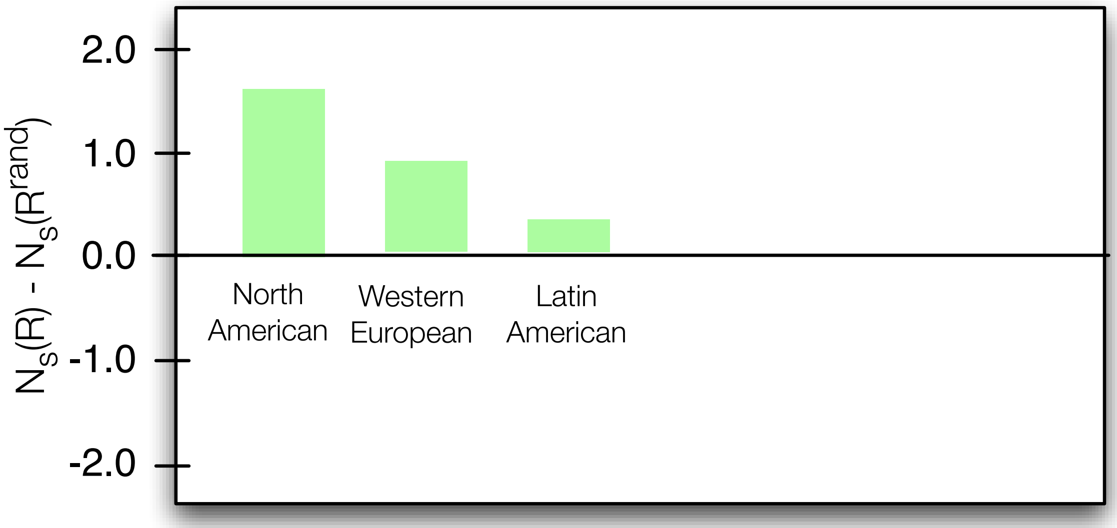
We can then **randomize** the recipes, and calculate:

$$N_s(R^{\mathrm{rand}}) = \frac{2}{n(n-1)} \sum_{i,j \in R^{\mathrm{rand}}} w_{ij}$$



Recipes

What we find is that there is indeed a tendency for ingredients in the same recipe to share compounds…



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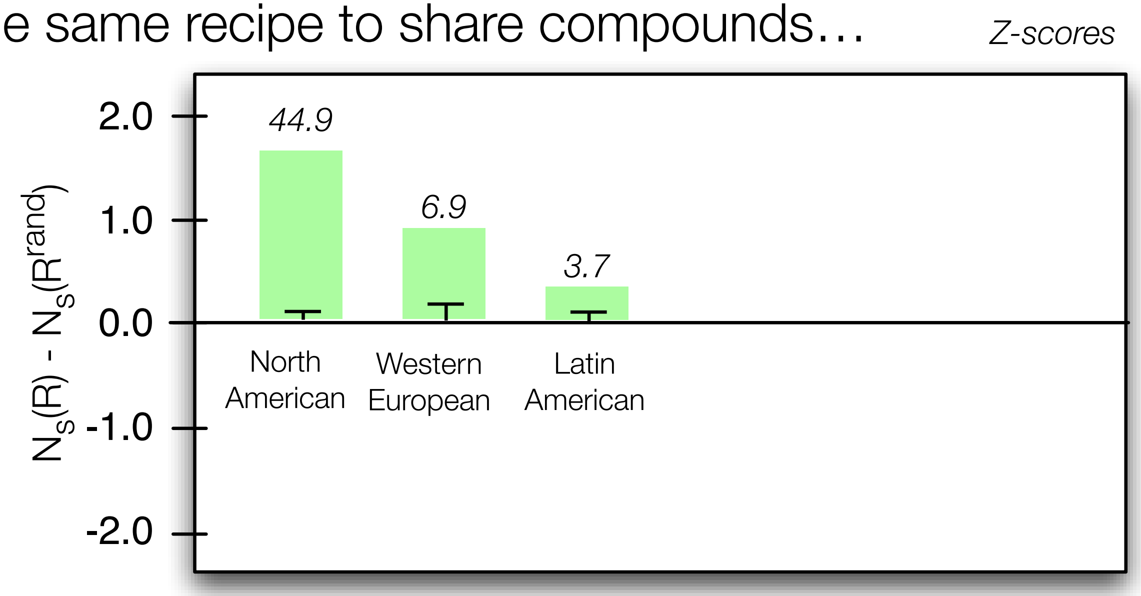

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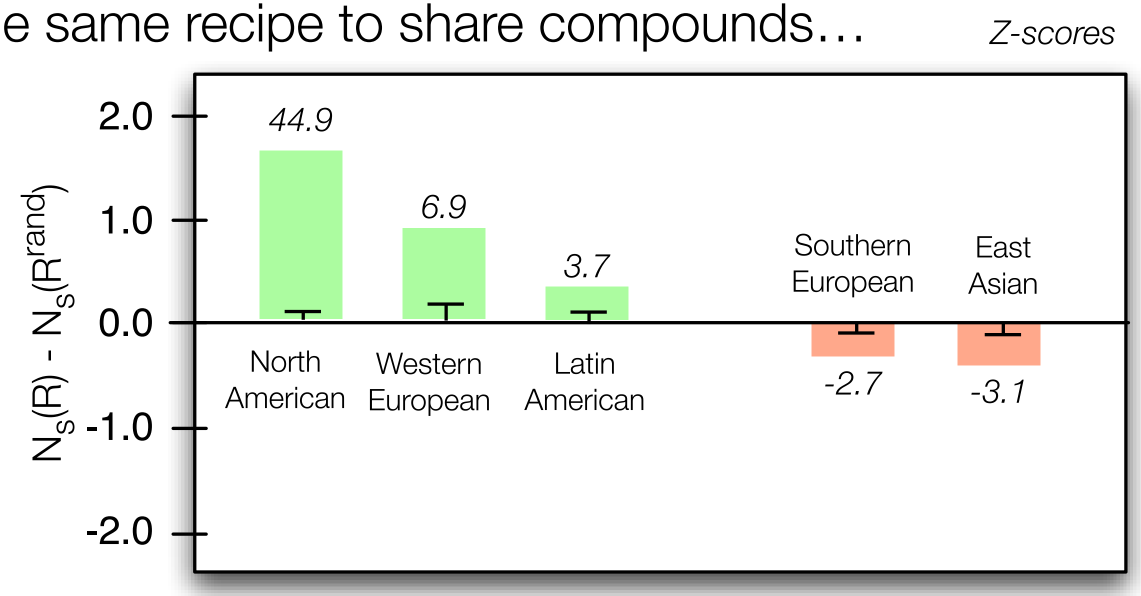

…and it is significant, but **only for certain cuisines!**

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- we are not using **concentrations** or detection/recognition **thresholds**

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- More details: **Ahn, Ahnert, Bagrow & Barabasi, Sci. Rep. 1, 196 (2011)**.

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- Odour and flavour **thresholds**
- Odour and flavour **descriptions** of compounds

The Flavour Bible

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The advantage this data set has over the recipes is that these pairings focus on **flavour**.

Volatile Compounds in Foods

The commercial **VCF** database contains **compound concentration** information on a large number of food ingredients.

We were kindly given access to this databases for research purposes by Ben Nijssen at TNO.

Odour and flavour thresholds

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This analysis however is not straightforward, as thresholds vary considerably depending on the medium the compound is in, among other factors.

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1-butanethiol	unpleasant (skunk) odour

OAVs and The Flavour Bible

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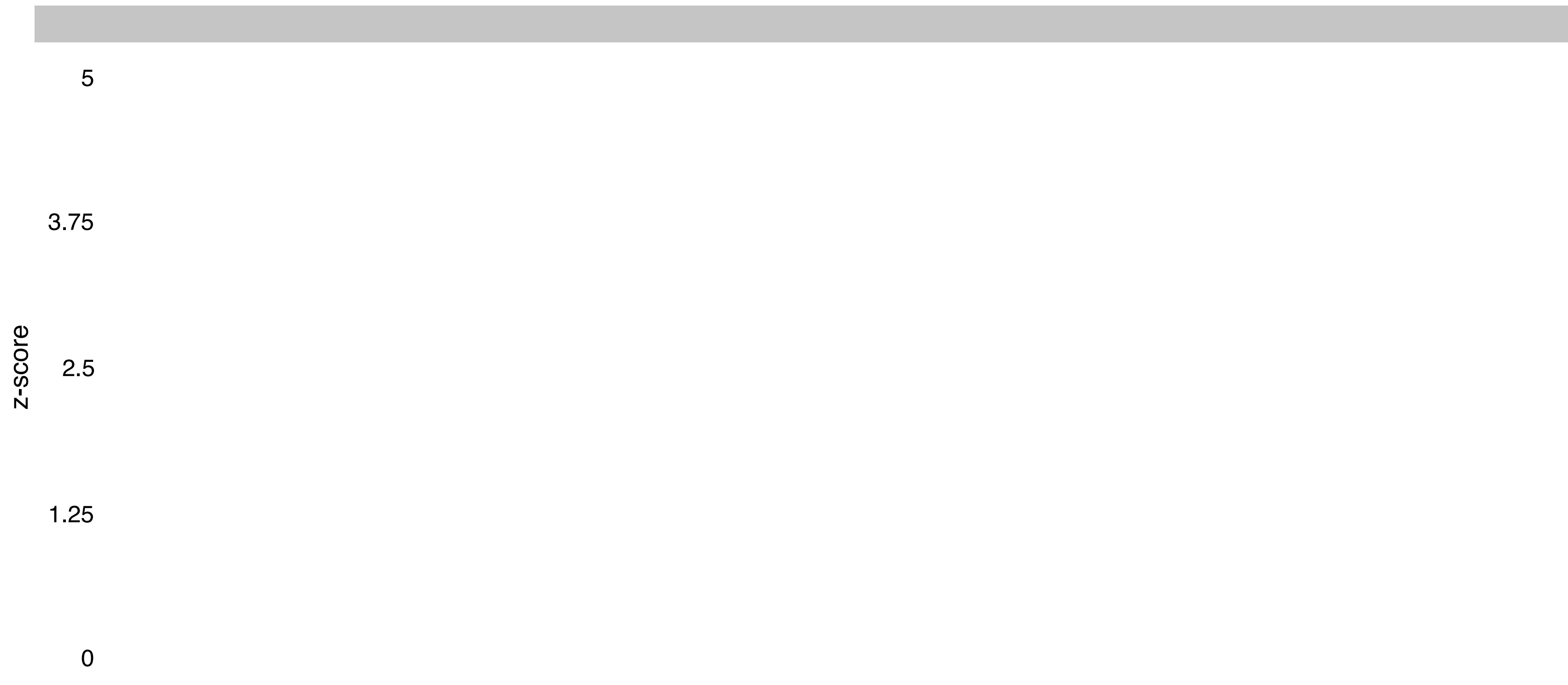
Like our recipe data, we randomised **The Flavour Bible** in order to see whether compatible food pairs shared more flavour compounds than expected by chance.

OAVs and The Flavour Bible



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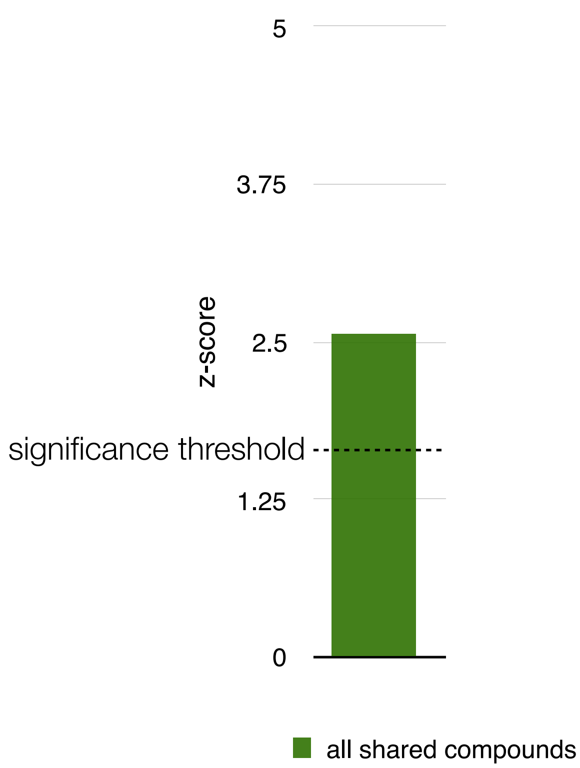

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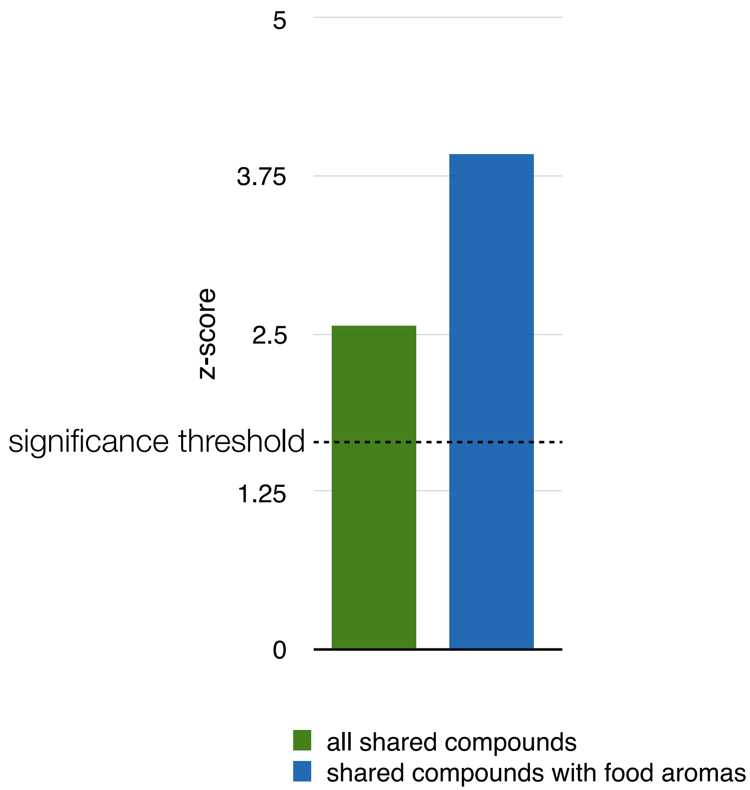

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If we limit ourselves to compounds that have **odours or flavours of foods**, we observe a higher significance score for the shared compound result.

Shared compounds V1.1

We can therefore formulate a modified version of the shared compound hypothesis:

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Two foods are more likely to taste good together if they share **dominant** chemical flavour compounds (OAV > 1), particularly if they have **food-related aromas**.

Shared olfactory receptors?

Why does the shared compound effect hold?

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One explanation is that shared compounds lead to the shared stimulation of **olfactory receptor neurons.**

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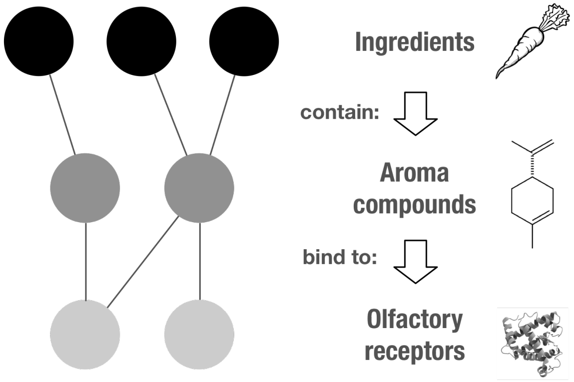
This is because each aroma compound binds to one or more out of several hundred **olfactory receptor proteins**.

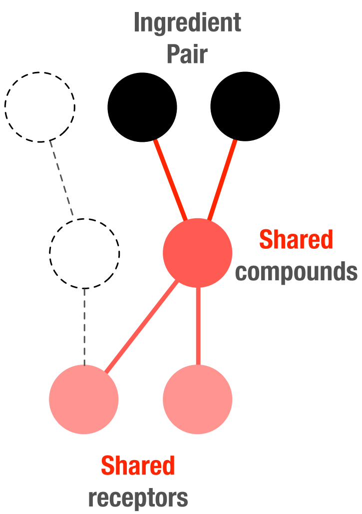
Each of these proteins is expressed in its specific type of olfactory receptor neuron, meaning there is a **one-to-one map** between proteins and neurons.

Shared olfactory receptors?



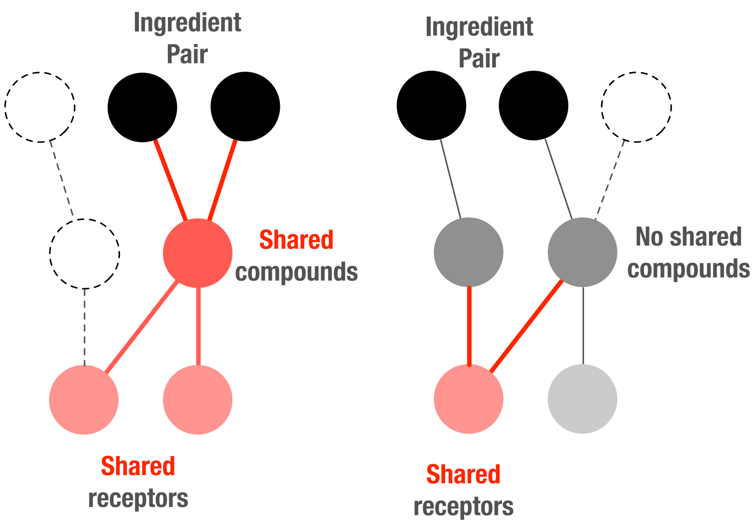
We now have a network with **three node types** – more specifically a tripartite network.

Shared olfactory receptors?



Ingredients can share **compounds**, which means they share **receptors**.

Shared olfactory receptors?



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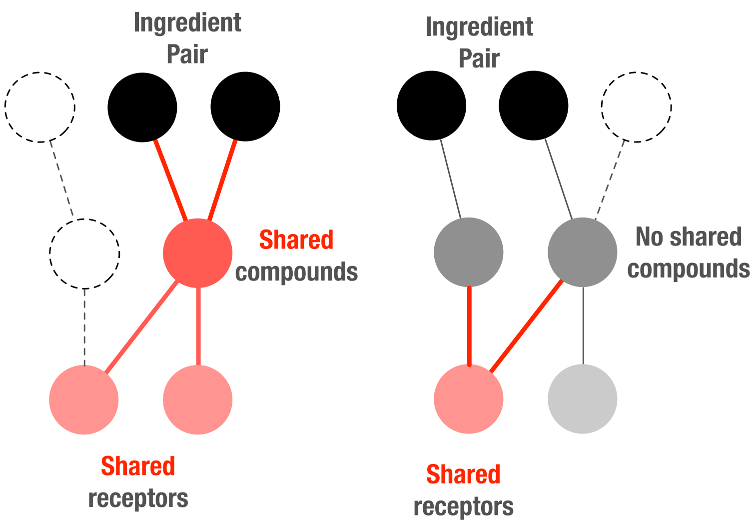
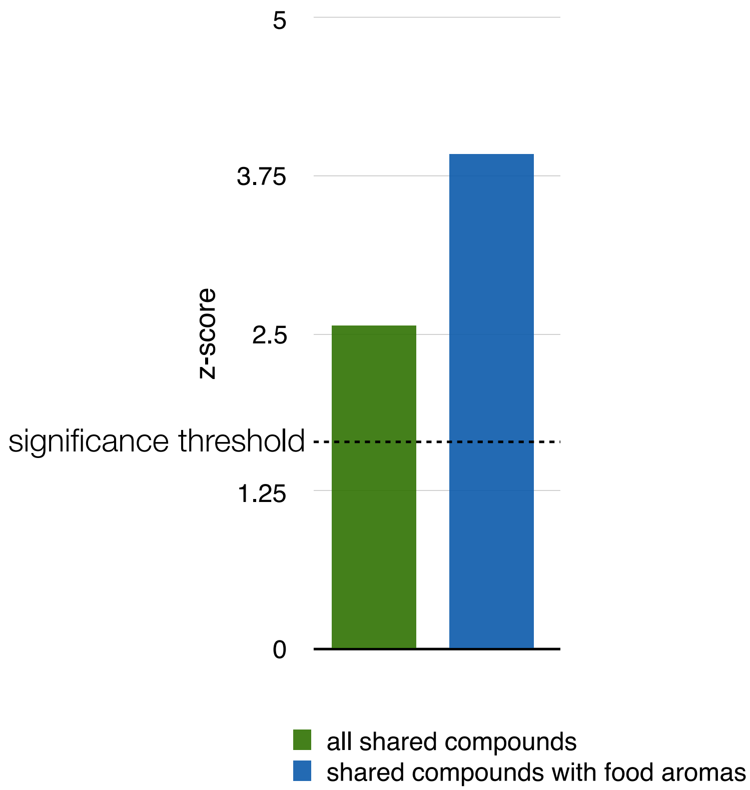


Receptors can be shared **even if compounds are not**.

Data on receptors is beginning to be available.

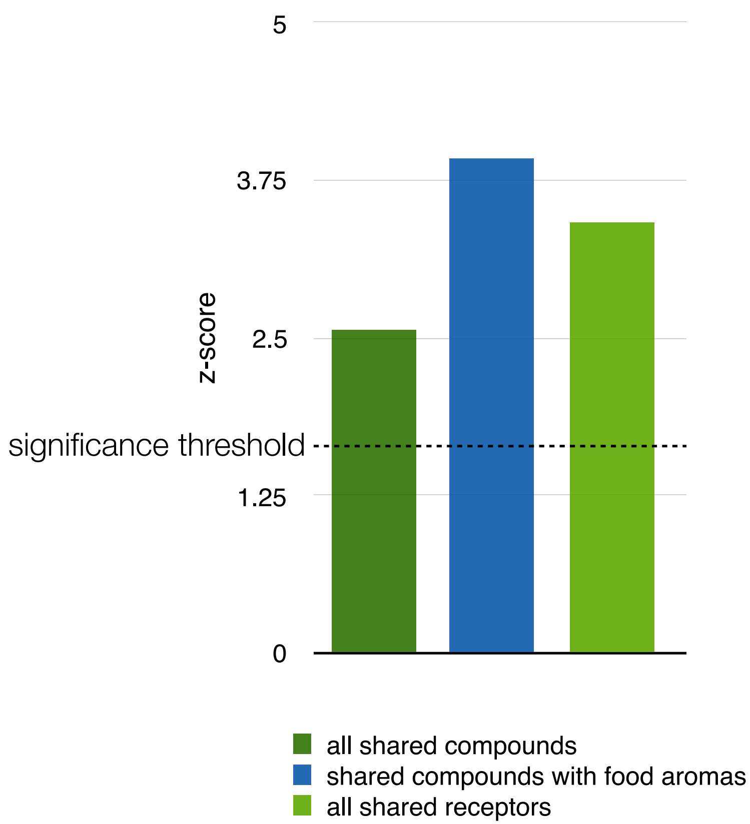
Dunkel, A. et al. *Angew. Chem. Int. Ed.* 53, 7124–7143 (2014)

The Shared Receptor Hypothesis



Comparing to our previous results let us now measure the number of **compound pairs that share receptors**.

The Shared Receptor Hypothesis



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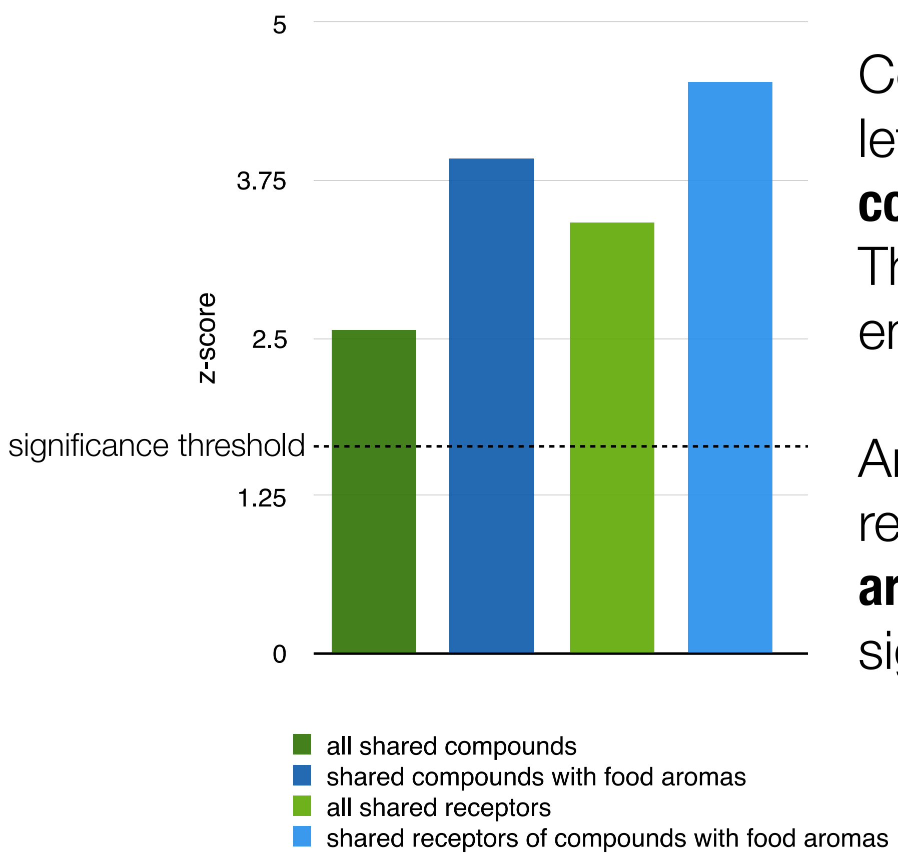
The Shared Receptor Hypothesis



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And if we only consider shared receptors for compounds **with food aromas**, the result is even more significant.

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By comparing this network to recipe databases we show that the **shared compound hypothesis holds true** for **some** regional cuisines. In other cuisines, an equally significant **inverse effect** appears to govern the flavour combinations chosen in recipes.

Conclusions

Using new data such as compound concentrations & thresholds, food pairing recommendations and compound descriptions we can show that foods taste good together if they share **dominant** chemical flavour compounds, and particularly those compounds **with food aromas**.

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The mechanism behind the shared compound hypothesis might be the fact that shared compounds mean **shared stimulation of olfactory receptor neurons**. We find some support for this hypothesis by showing that **shared receptors are even more significantly enriched** than shared compounds.

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So perhaps **computational gastronomy** is next?

Thank you for your attention!

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