

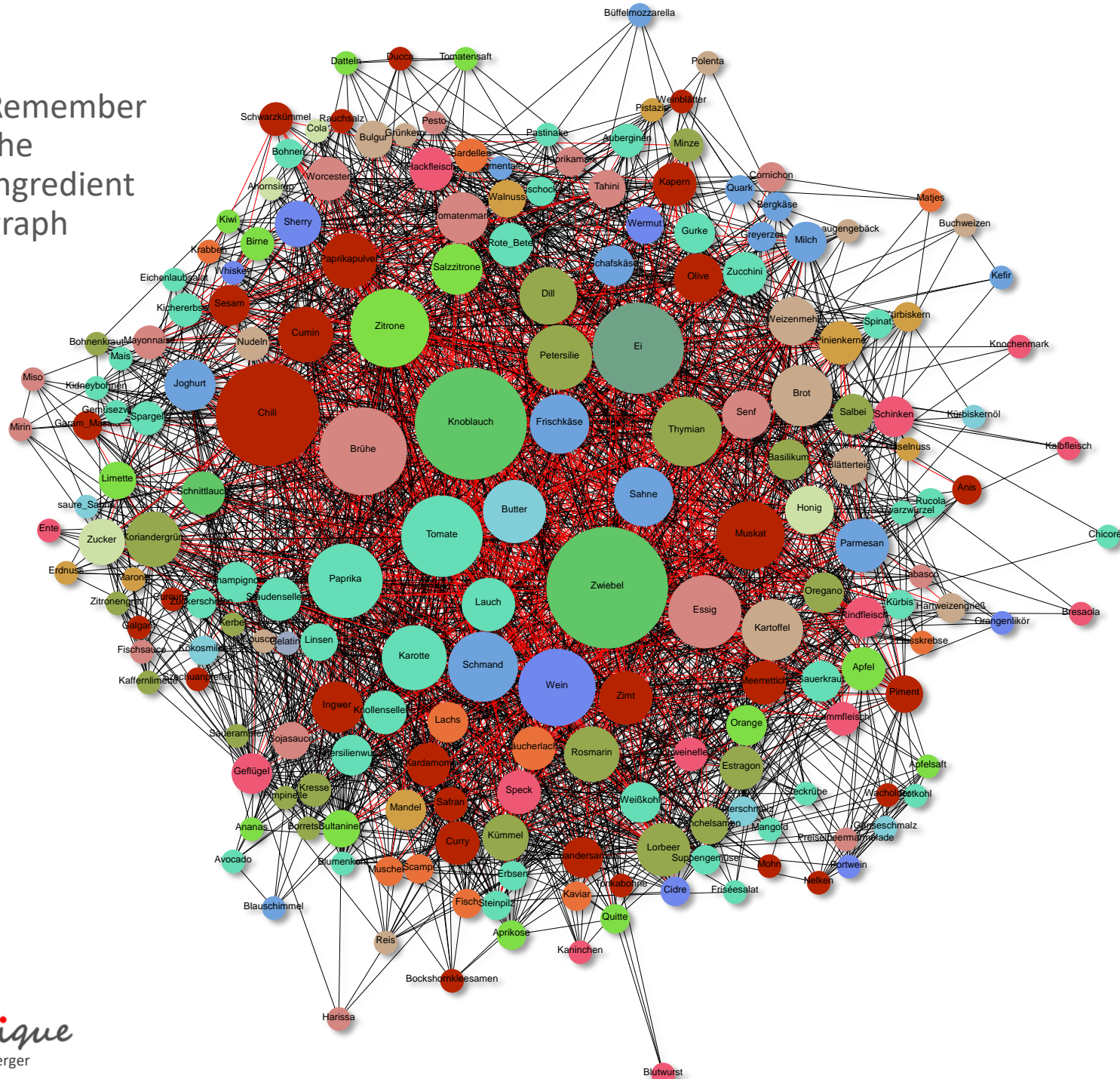
fruschtique

by Norbert Luttenberger

Culinary Interpretation

What ingredient graphs can tell

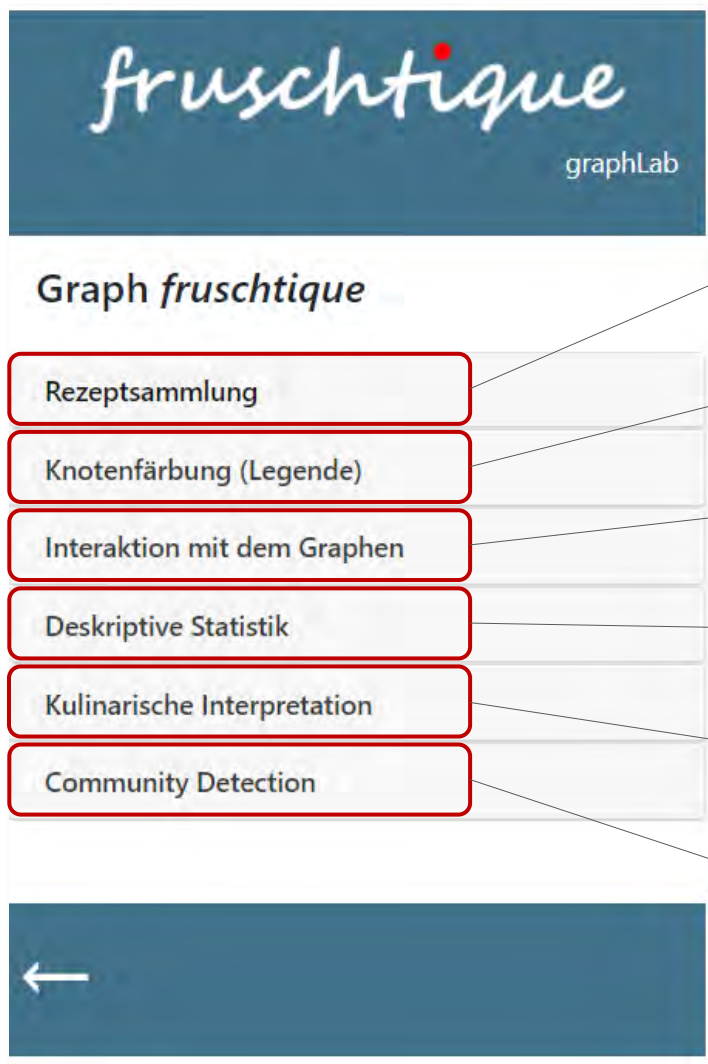
Remember
the
ingredient
graph



Descriptive statistics for
ingredient graphs

Dedicated statistics for
culinary interpretation

Viewer page



short description of the graph data source

legend for graph coloring

modes for direct user interaction with graph

descriptive statistics for the graph, [see below](#)

culinary interpretation of the graph, [see below](#)

community detection, under preparation



Graph-theoretic interlude

Basic definitions

A **graph** G is an ordered pair (V, E) , where V is called the **set of vertices**, and E is called the **set of edges** of G .

graph

V is a **finite set** and $E \subseteq \binom{V}{2}$ or $E \subseteq \{X \subseteq V: |X| = 2\}$
is a **set of pairs of elements in V** .

vertices, edges

The edge $e = \{u, v\} \in \binom{V}{2}$ is also denoted by $e = uv$.

If $e = uv \in E$ is an edge of G , then u is called **adjacent** to v .

adjacent

If the vertex u is on edge e , the vertex u is said to be **incident** on e .

incident

Some graph types

A **directed graph** is a pair $G = (V, A)$, where V is a finite set and $A \subseteq V \times V$.

The edges of a directed graph are also called arcs. A directed graph is different from an undirected graph in that an arc is defined by an ordered pair (u, v) of two nodes. This definition allows us to distinguish arc (u, v) going from node u to node v from arc (v, u) going from v to u .

directed graph

A weighted or **edge-labeled** graph can be defined as a triple $G = (V, E, w)$ where $w: E \rightarrow \text{val}$ is a function mapping edges to their values. For edge-labeled graphs val can be any type. We talk about edge-colored graphs, if val is restricted to $\mathbb{N} \setminus \{0\}$. The same applies to **node-labeled** graphs.

weighted graph

A **simple graph** (or just graph), is an unweighted, undirected graph containing no graph loops or multiple edges.

simple graph

A **complete graph** is a graph in which each pair of vertices is connected by an edge, i.e., a graph in which each pair of vertices are adjacent is a complete graph.

The complete graph with n vertices is denoted K_n and has

$$\binom{n}{2} = \frac{1}{2} n \cdot (n - 1) \text{ edges.}$$

complete graph

A multigraph is a pair $G = (V, E)$ where V is a finite set and E is a multiset of elements from $\binom{V}{2} \cup \binom{V}{1}$, i.e., we also allow **multiedges and loops**.

multigraph

Ingredient graph

An ingredient graph $IG = (V, E, w, c, o)$ is an undirected, loop-free, weighted, and node-labeled graph where

- V is a finite set of ingredient nodes identified by their ID and
- $E \subseteq \binom{V}{2}$ is a set of edges.
- w is a function that assigns a weight value from $\mathbb{N} \setminus \{0\}$ to each edge,
- c is a function that assigns a class value to each node, where this value comes from $class = \{alc, carb, condi, egg, etc, fat, fish, fruit, herb, meat, milk, nuts, onion, spice, sweet, veg\}$
- o is a function that assigns an occurrence value ω to each node with $\omega \in \mathbb{N} \setminus \{0\}$.
- The occurrence value can easily be transformed into a prevalence value by dividing it by the number of recipes in the collection under scrutiny.



Descriptive statistics

Viewer page



descriptive statistics for the ingredient graph

Two views on descriptive statistics for ingredient graphs

Graph-oriented

- Exploit structural properties of the ingredient graph
- Examples: Degree, betweenness, ... of ingredient nodes

Recipe-oriented

- Relate back to contributing recipe(s) (kind of inverted index approach)
- Example: Ingredient prevalence

Ingredient prevalence

ingredient
prevalence

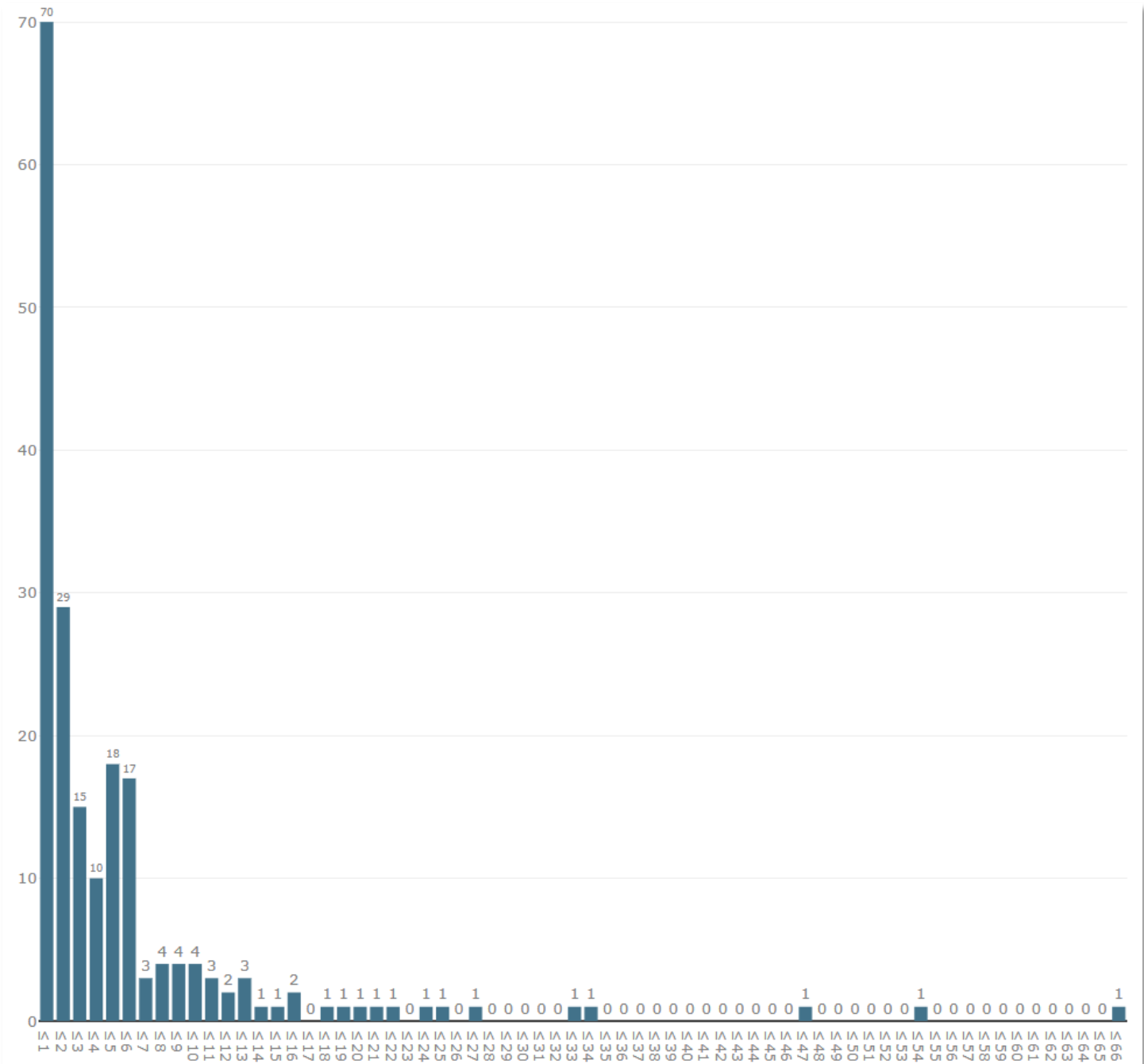
$$prev_{igt} = \frac{\#rcps \text{ using } igt}{\#rcps}$$

computed from occurs value contained in
ingredients section of combinedGraph.json

typically: few high, many low values;
"long tail"

gives hint to diversity of collection

occurs
values
histogram



Ingredient node neighbors

ingredient
node
neighbours

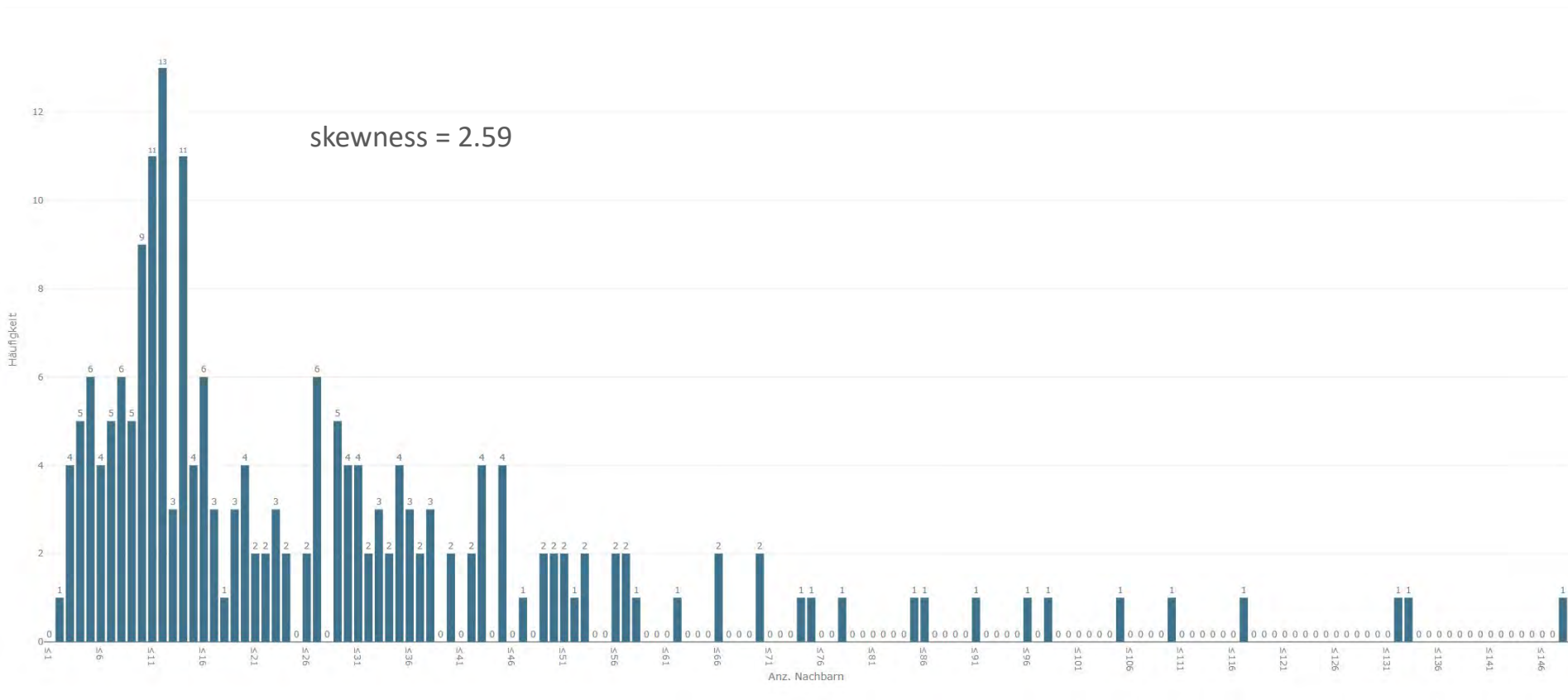
#nodes adjacent to selected node

computed from ingredient graph

typically: more high than low values;
right-skewed

gives hint to which ingredients
are combined with a selected ingredient

Node neighbours histogram



Ingredient node degree

ingredient
node
degree

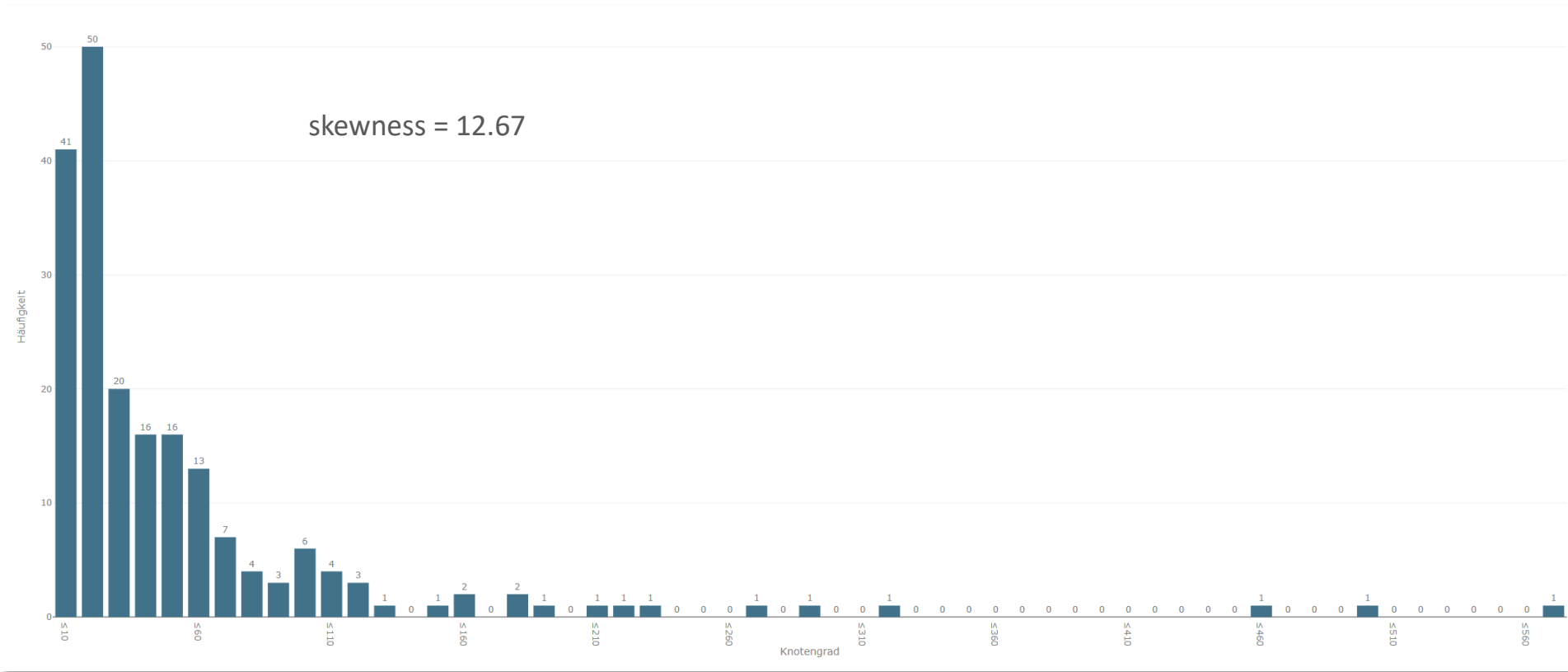
The degree of a vertex v of G , denoted by $d(v)$ or $\deg(v)$, is the number of edges incident to v .

computed from ingredient graph

typically: more high than low values;
highly right-skewed

gives hint to which ingredients
are strongly/weakly related to others

Node degree histogram



Ingredient node betweenness

ingredient
node
between-
ness

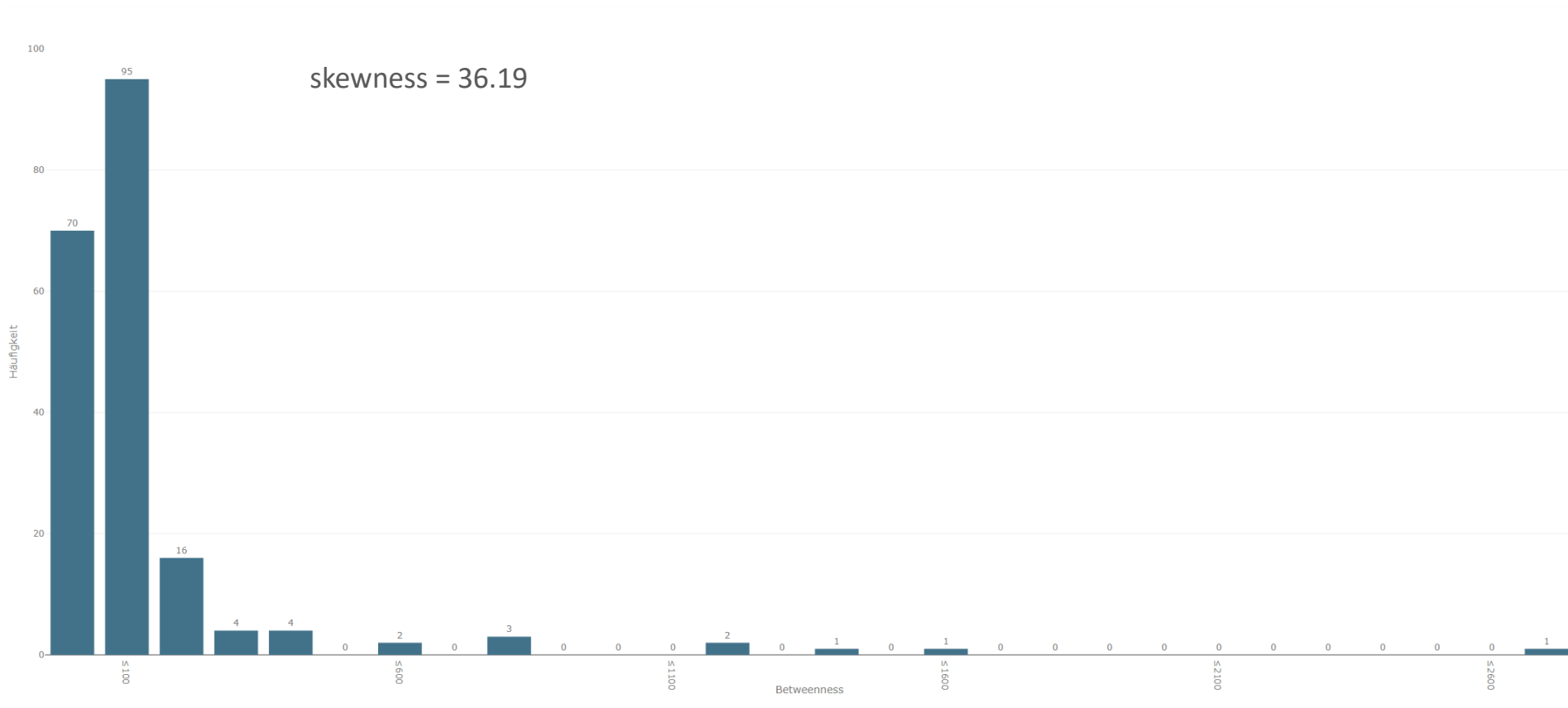
Betweenness Centrality for a vertex $v \in V$ in a connected graph $G = (V, E)$ is given by $\sum_{s,t \in V \wedge s \neq v \wedge t \neq v} n_{s,t}^v / n_{s,t}$, where $n_{s,t}$ is the number of shortest paths from s to t and $n_{s,t}^v$ is the number of shortest paths from s to t passing through v .

computed from ingredient graph

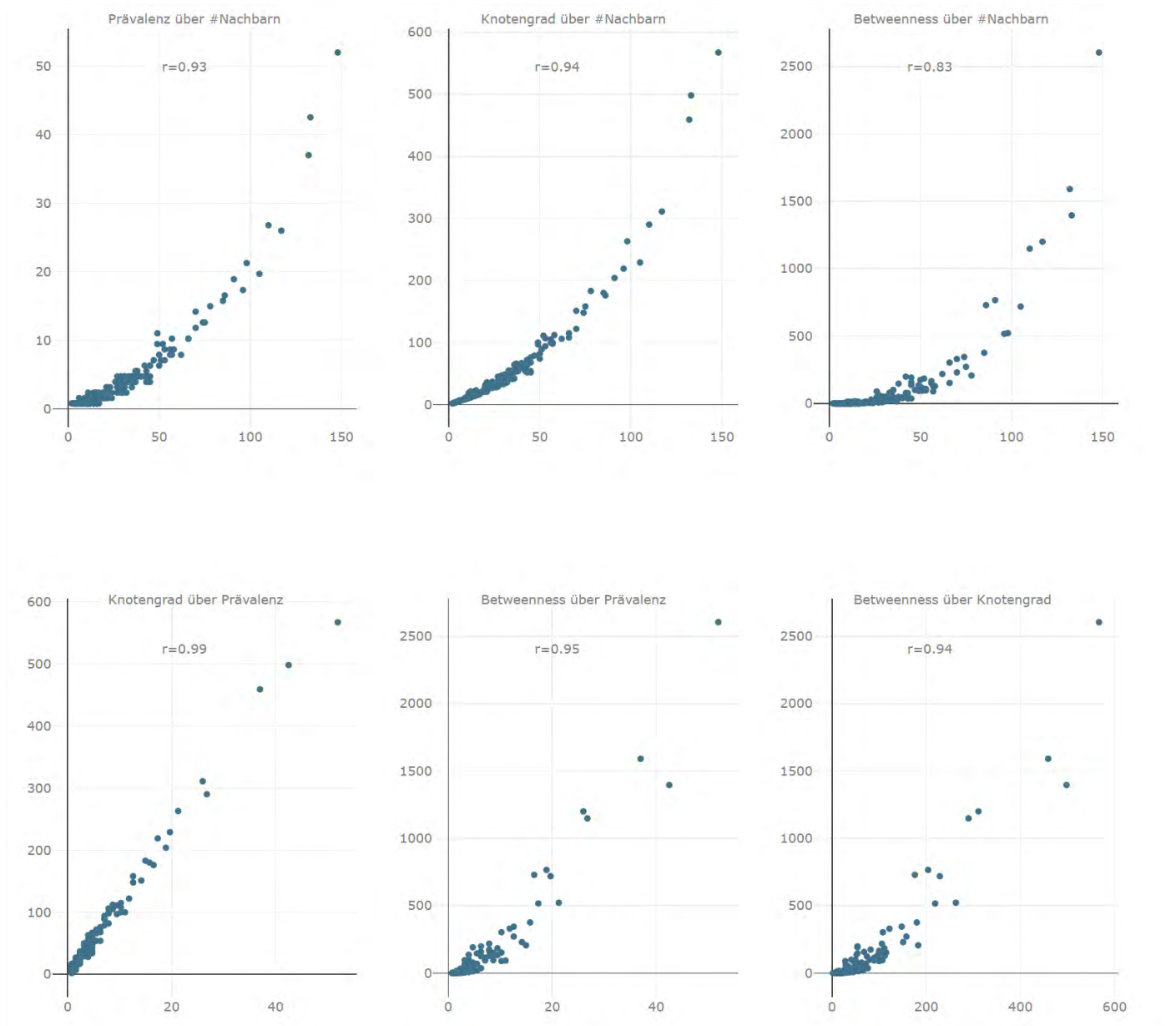
typically: more high than low values;
highly right-skewed

gives hint to which ingredients
may serve as "intermediators" between others

Node betweenness histogram, sample



Mutual correlations



Mind the high correlation coefficient values!

for above sample:

prevalence	–	#node neighbours	0.93
node degree	–	#node neighbours	0.94
betweenness	–	#node neighbours	0.83
node degree	–	prevalence	0.99
betweenness	–	prevalence	0.95
betweenness	–	node degree	0.94

Ingredient relations

ingredient
relations

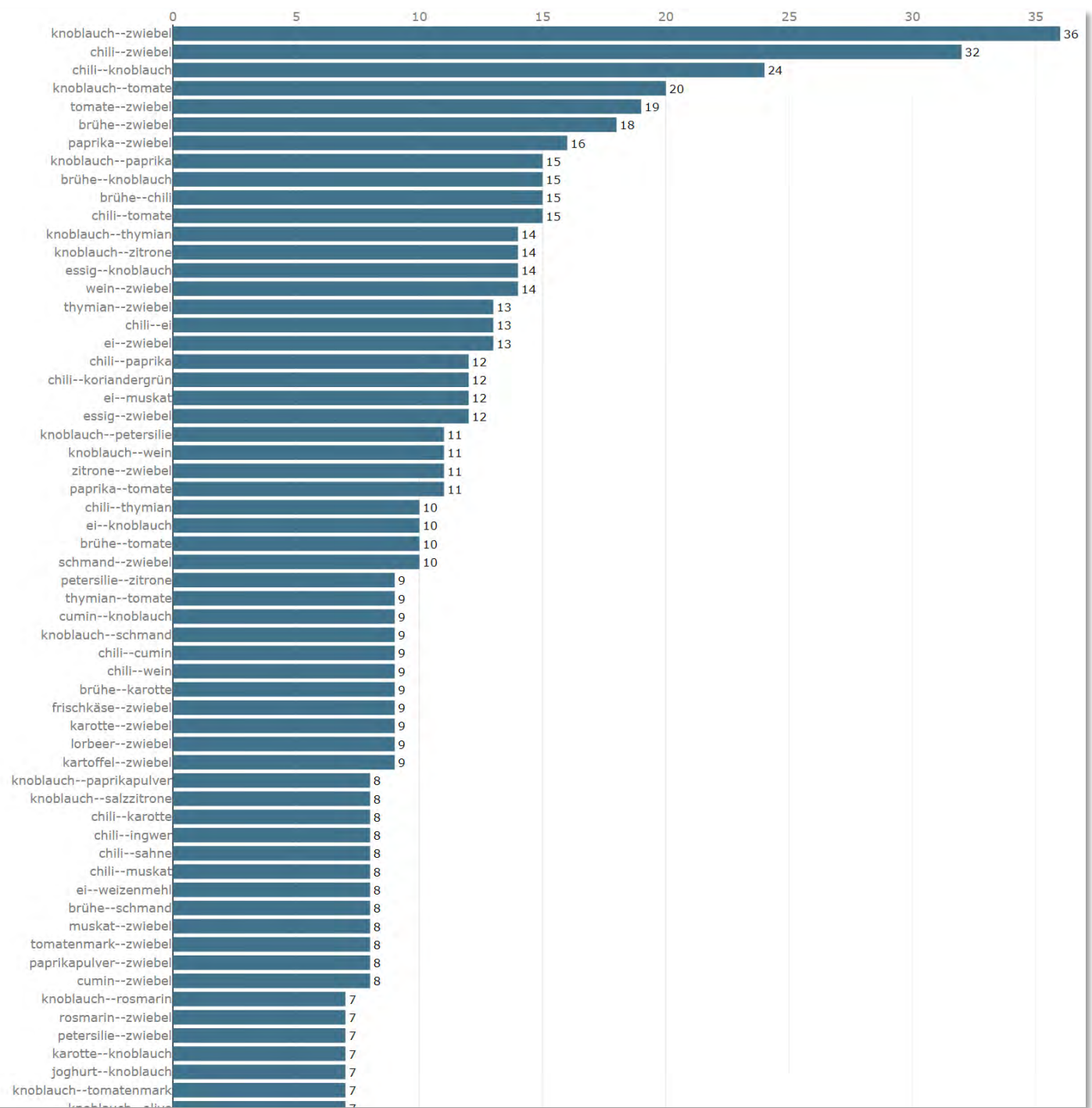
Ingredient graph edges including their weight values

computed from ingredient graph

typically: more high than low values;
"long tail"

gives hint how ingredients
are related to one another

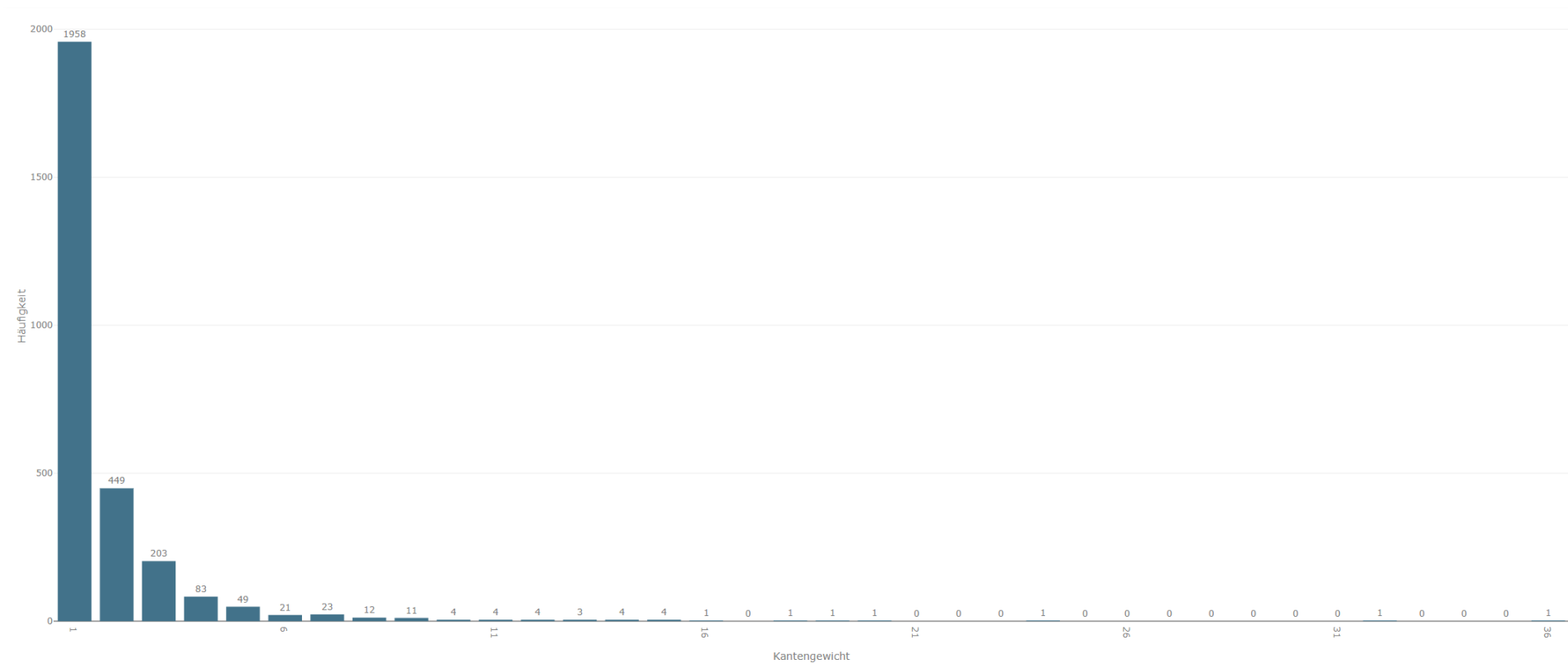
Ingredient relations bar chart (highest values)



Ingredient relations bubble chart (highest values)



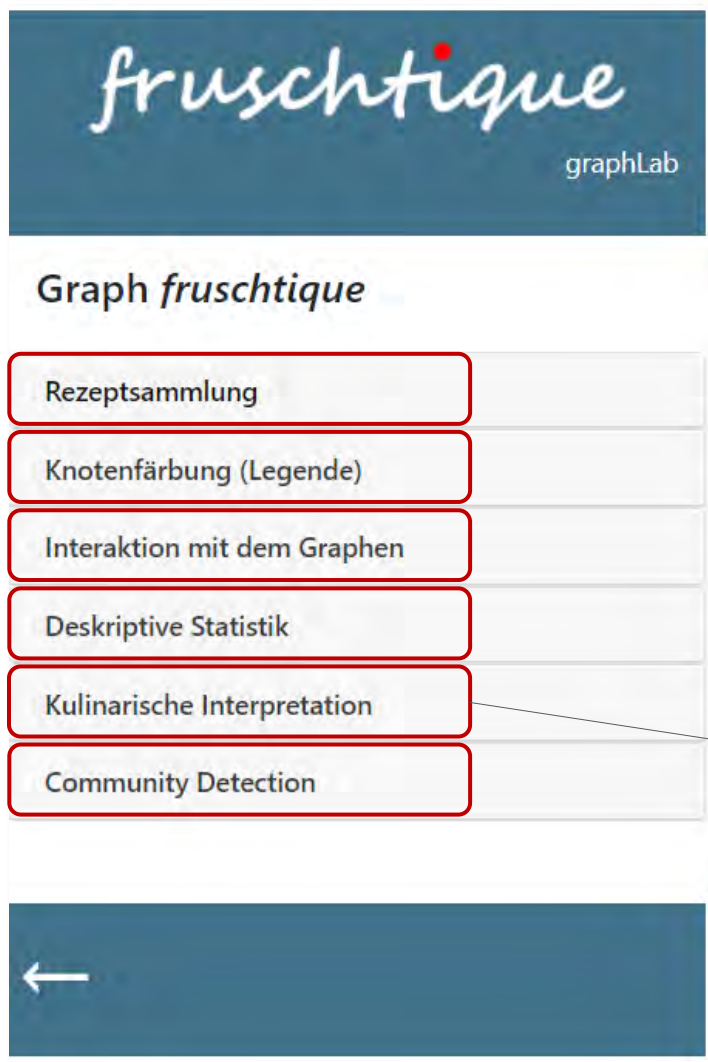
Ingredient relation weight histogram





Culinary interpretation

Viewer page

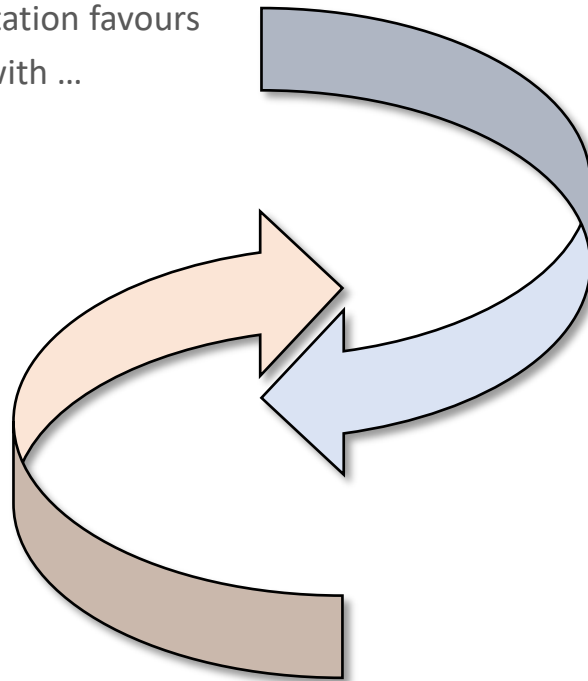


culinary interpretation of the ingredient graph

Caveat

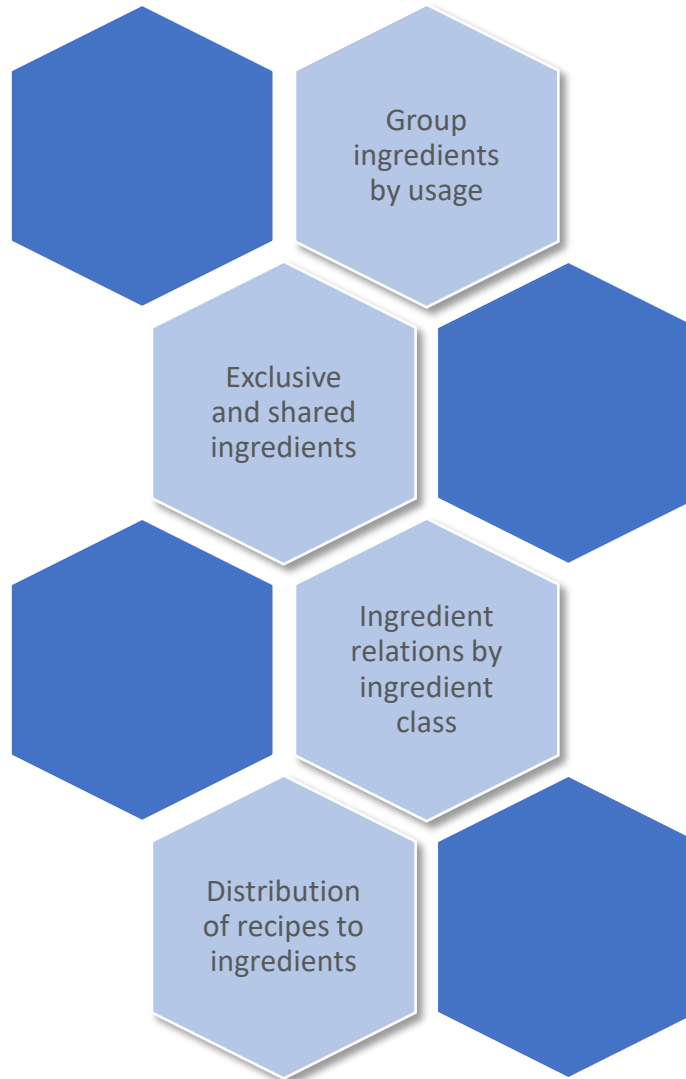
My culinary interpretation favours
culinary collections with ...

diversity in
seasoning

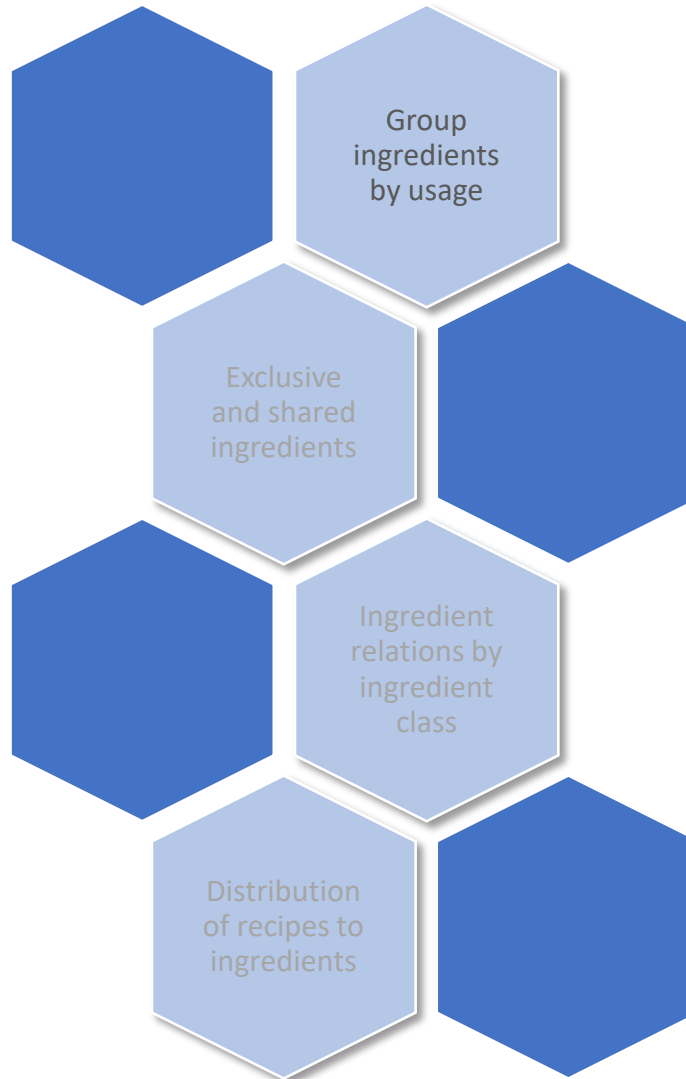


diversity in
ingredients and
ingredient combinations

Making it visible



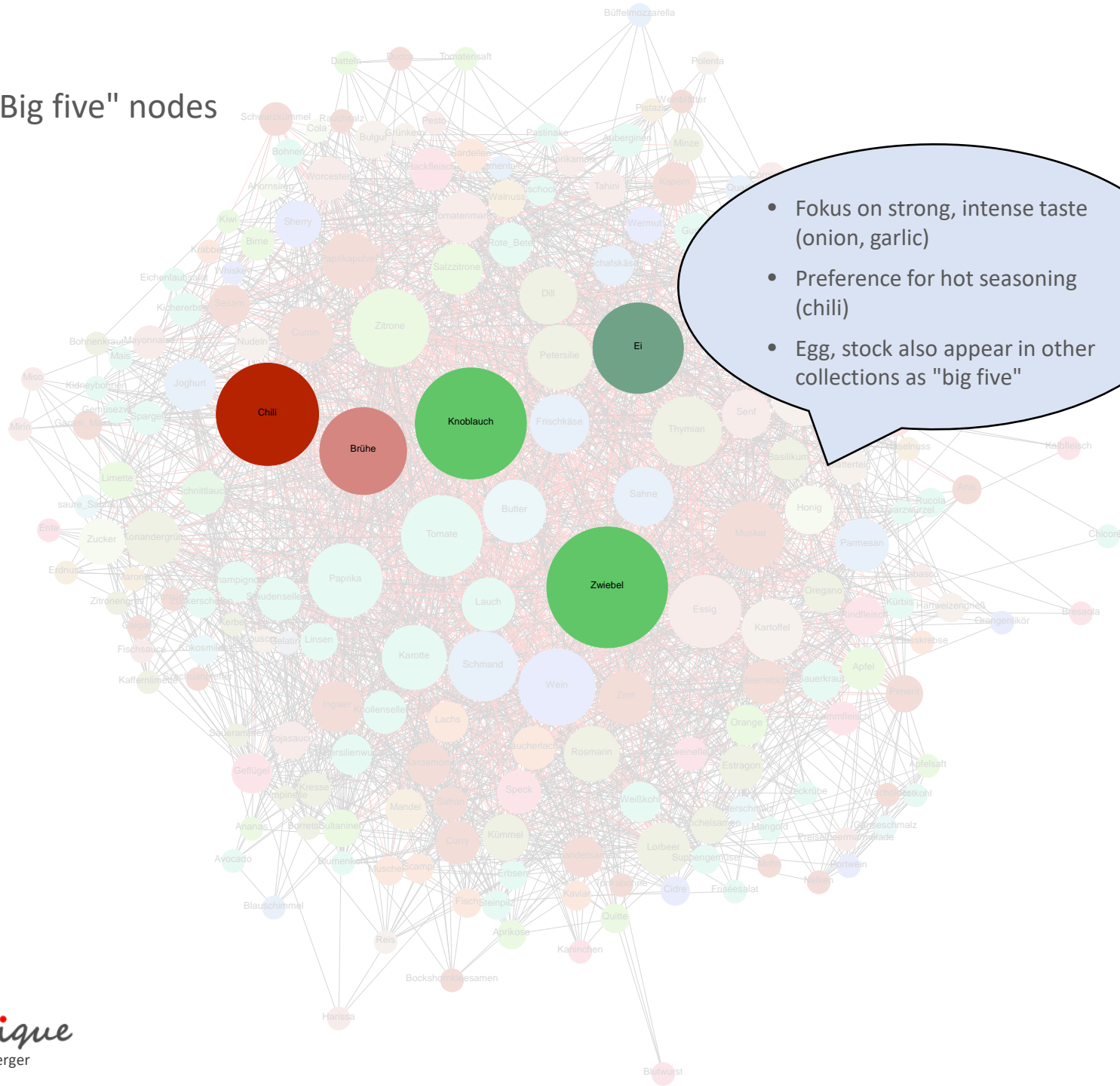
Making it visible



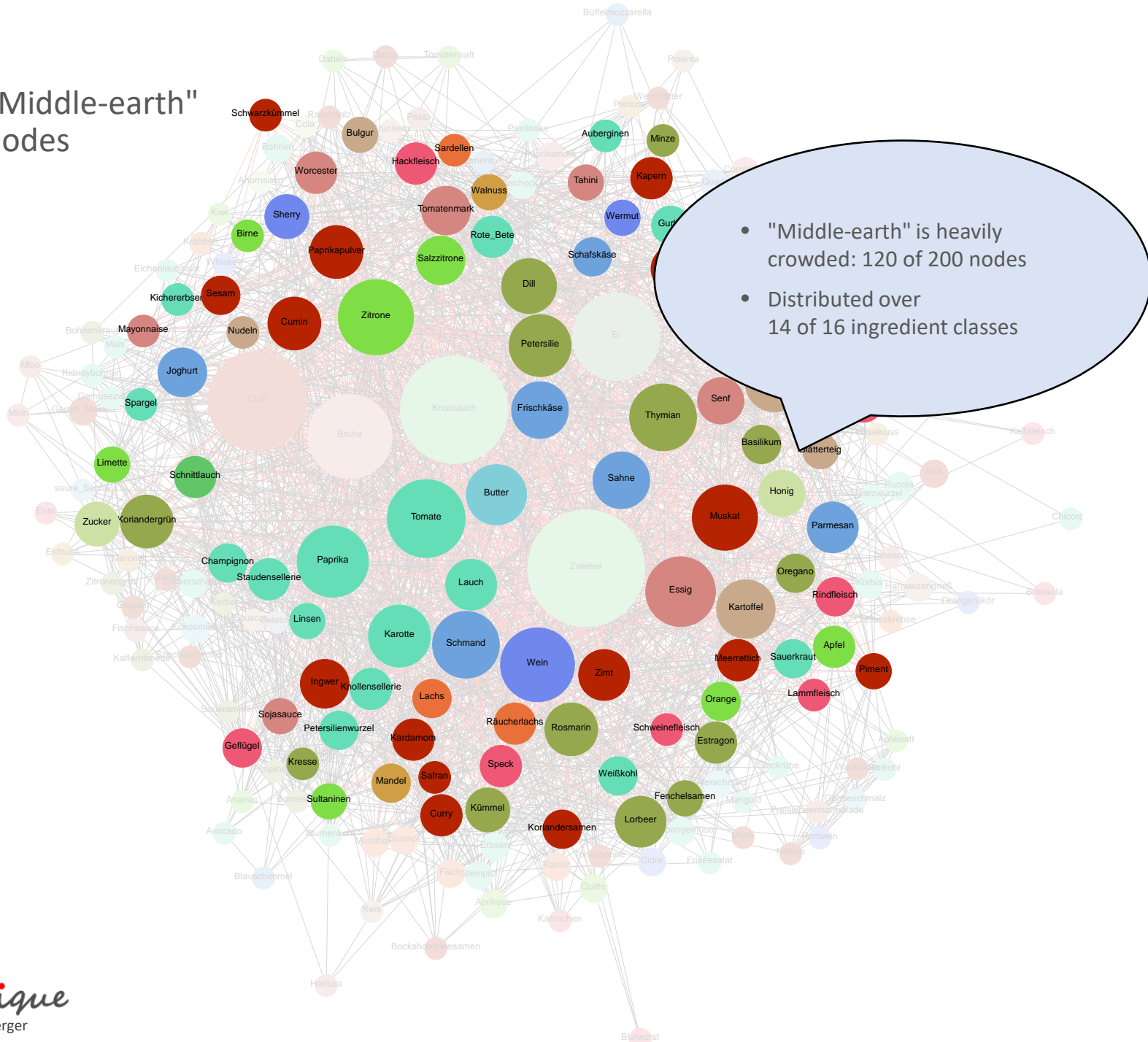
"Degree of usage" groups



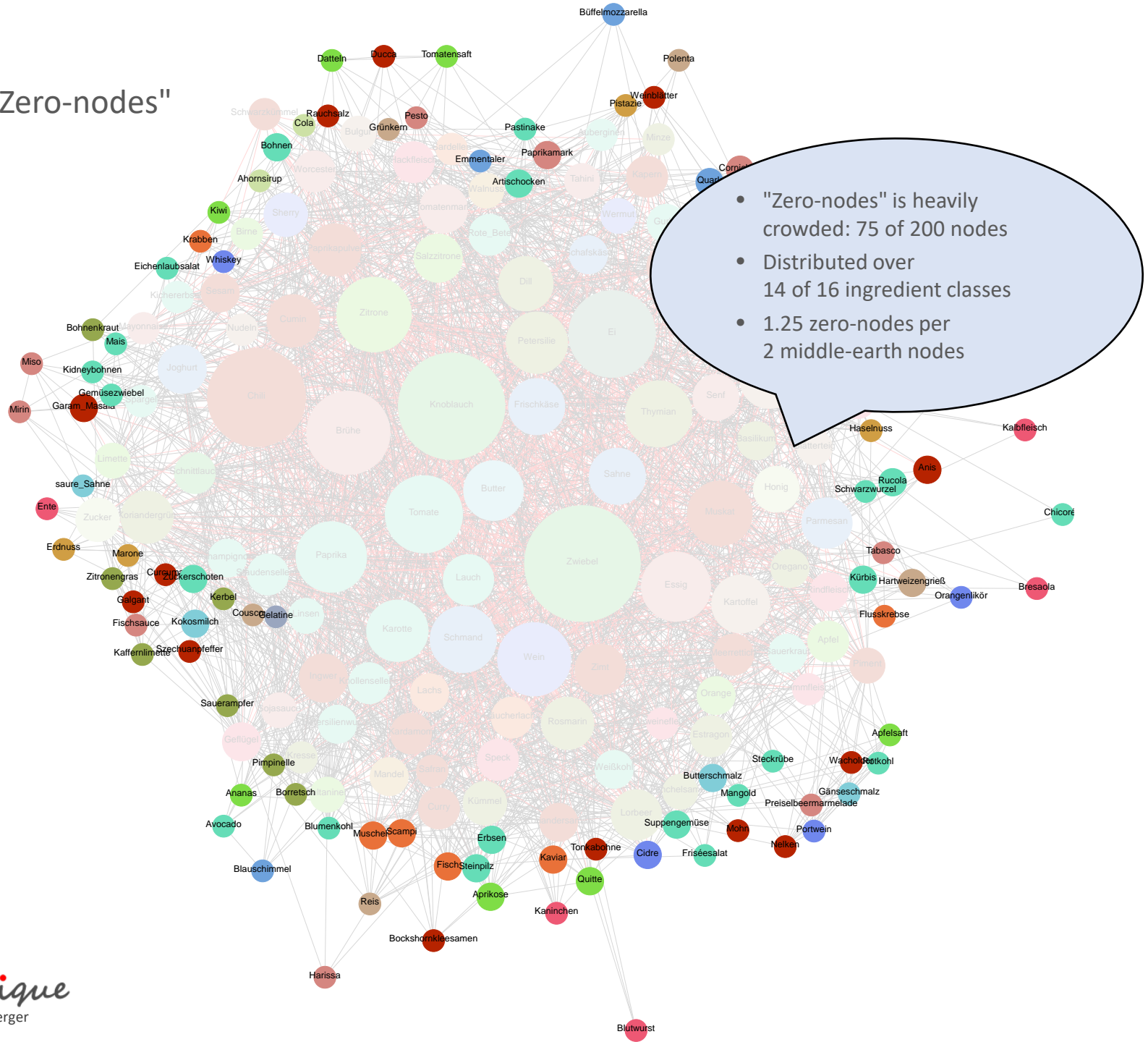
"Big five" nodes



"Middle-earth" nodes



"Zero-nodes"



Ingredient classes vs. degree of usage

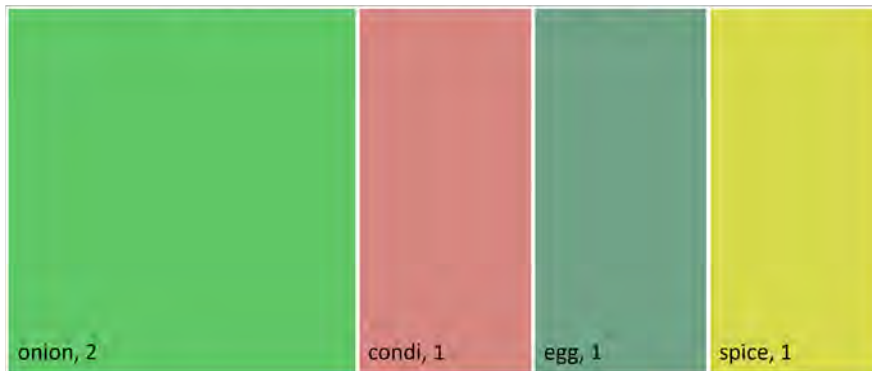
Ingredient Class Population total



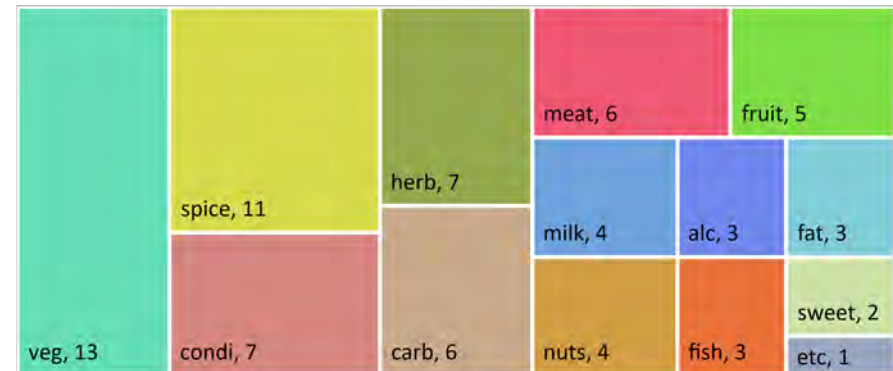
Ingredient Class Population "Middle-earth"



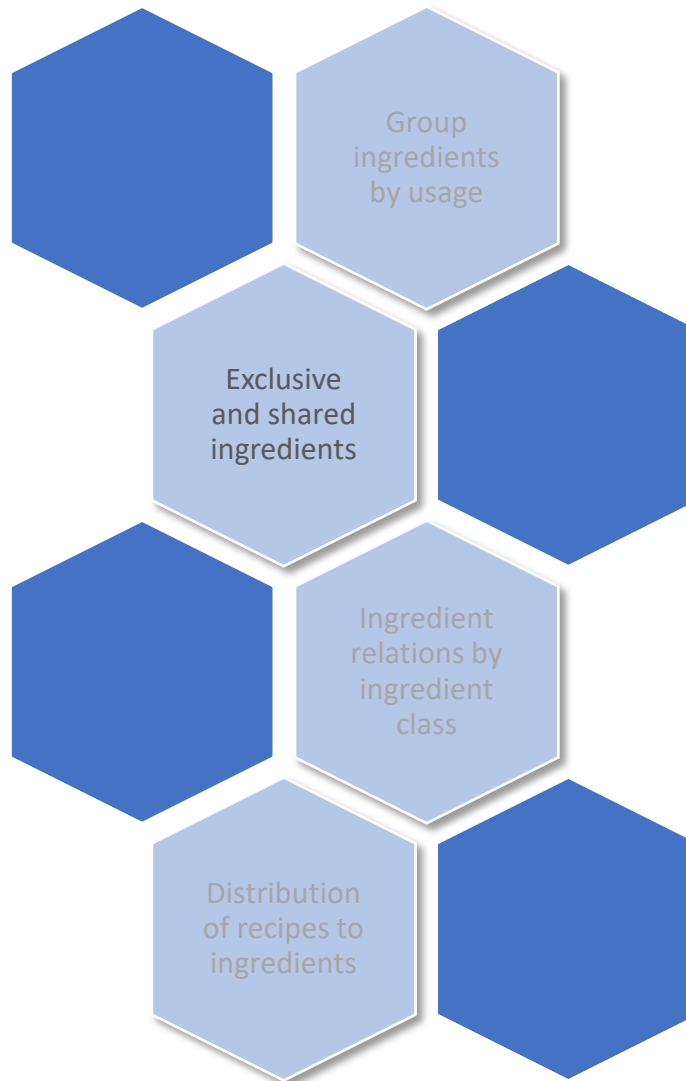
Ingredient Class Population "Big Five"



Ingredient Class Population "Zero-nodes"



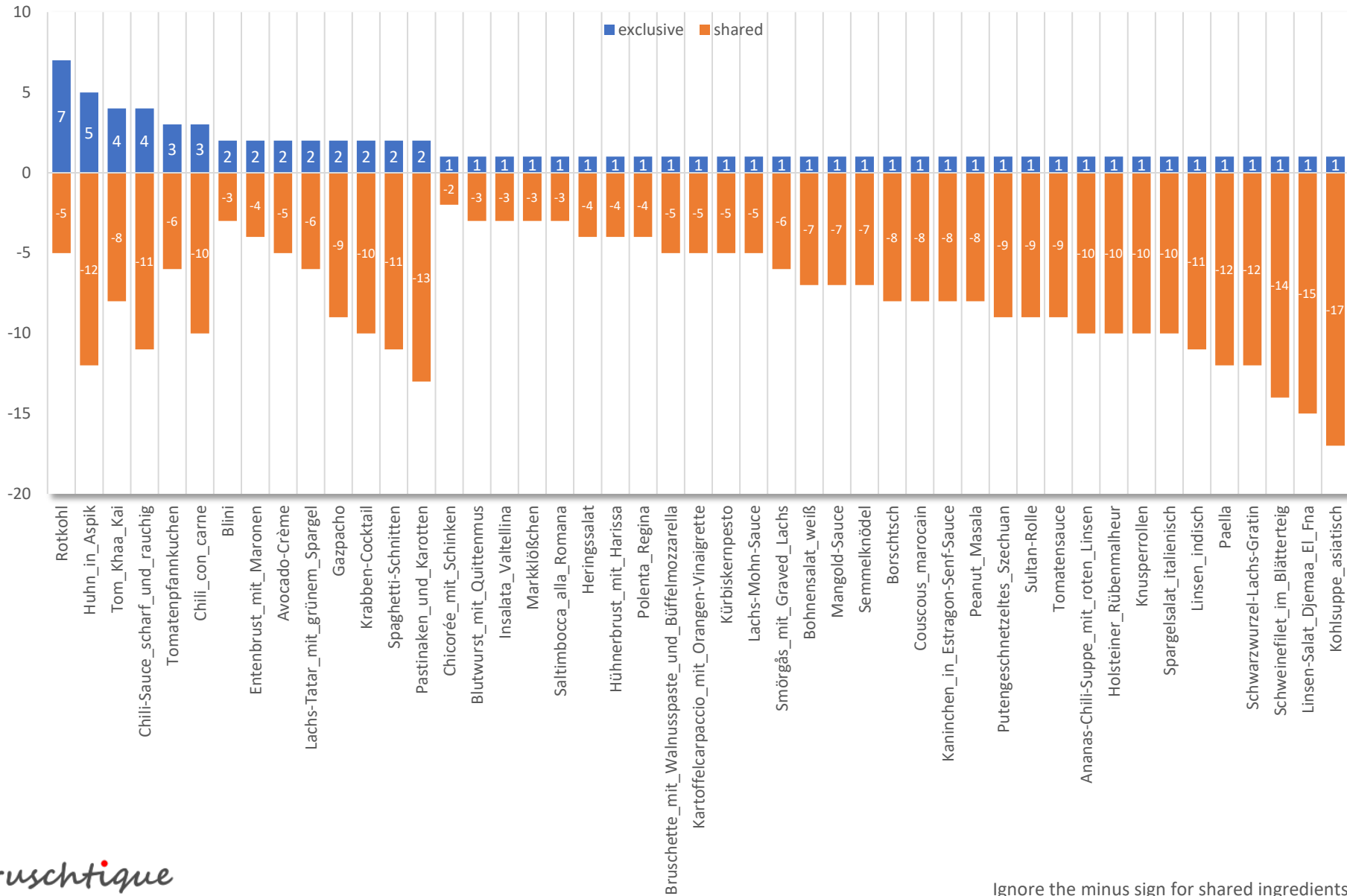
Making it visible



Exclusive vs. shared ingredients

- If an ingredient is used in only one recipe, it is called an **exclusive** ingredient. Exclusive ingredients have an **occurrence value = 1**.
- If an ingredient is used in more than one recipe, it is called a **shared** ingredient. Shared ingredients have an **occurrence value > 1**.
- Favor recipes that use a high number of exclusive ingredients and a low number of shared ingredients.

Exclusive vs. shared ingredients



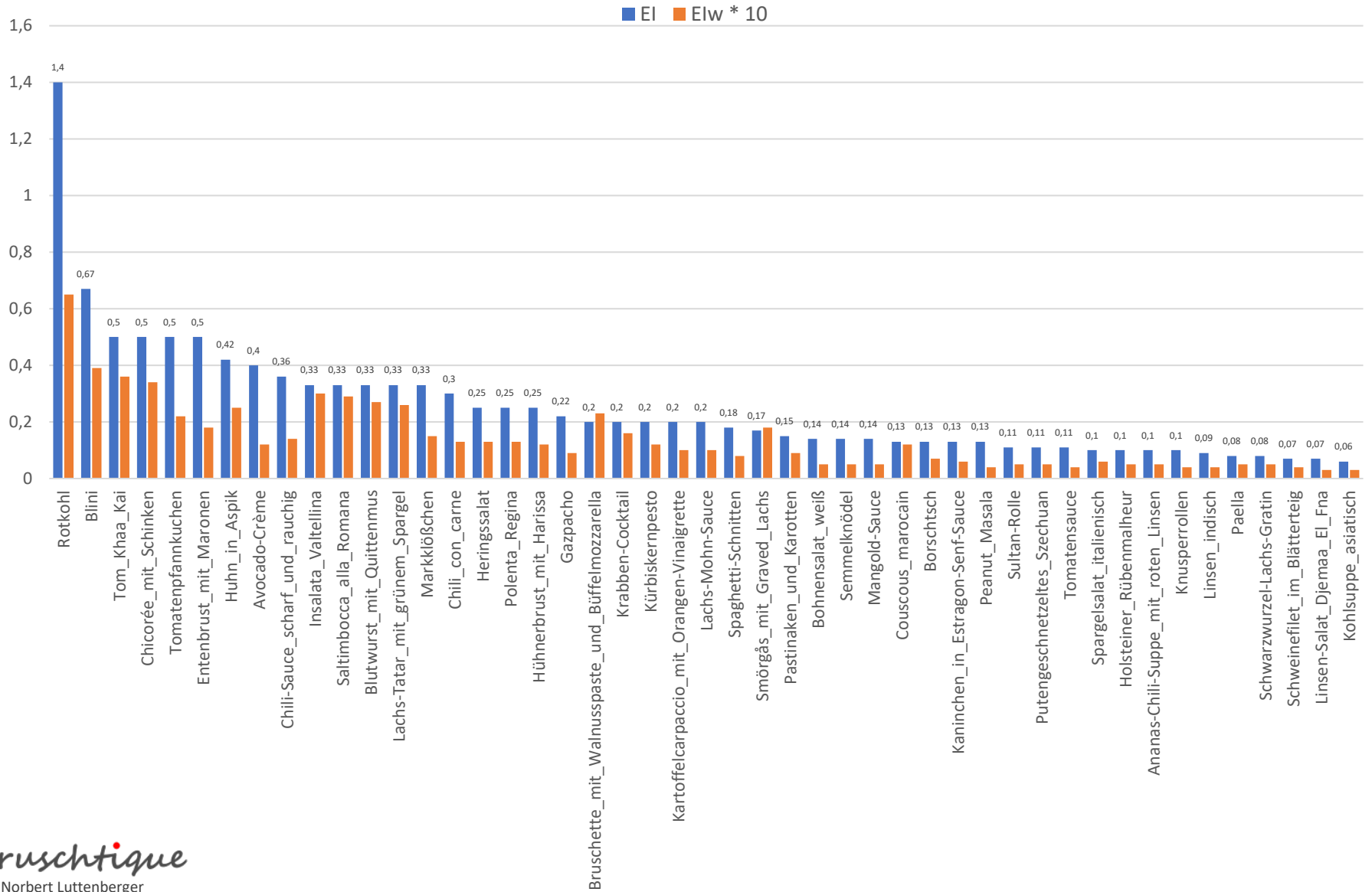
Exclusive vs. shared ingredients again

- For numerical comparison, compute a so-called **El number** per recipe.
- The El number comes in two variants:

EI number of exclusive ingredients in recipe
divided by number of shared ingredients in recipe

EI_w weighted El number:
number of exclusive ingredients in recipe
divided by sum of shared ingredient occurrence values in recipe

El and El_w



Two findings



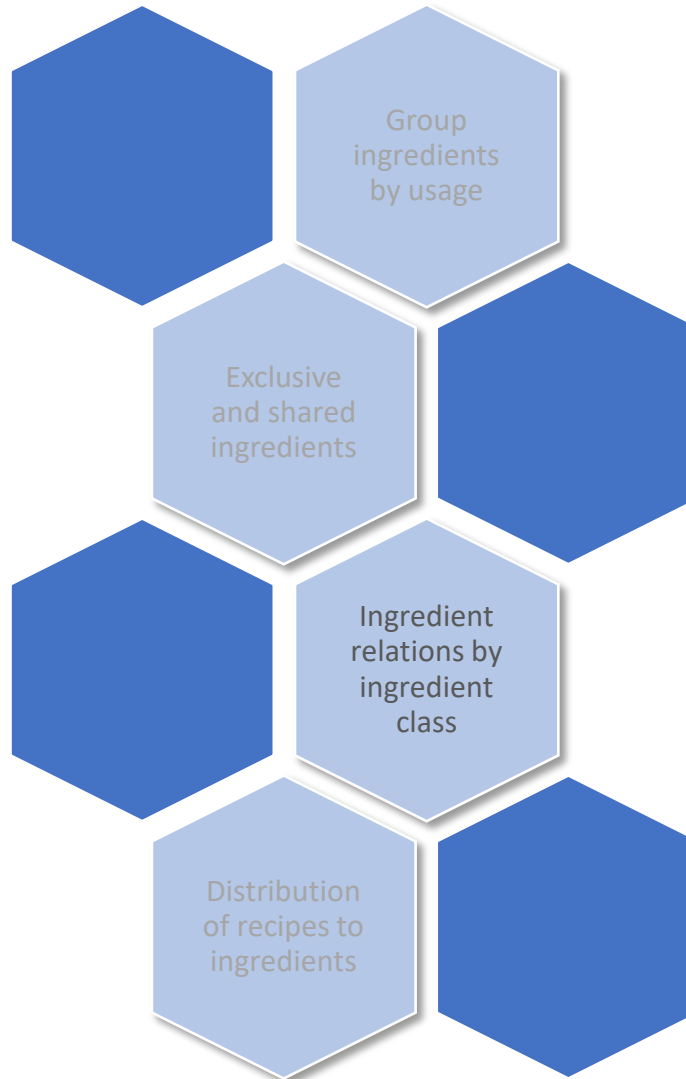
$$EI_w * 10 > EI$$

Bruschette	occ
brot	14
walnuss	4
kapern	6
petersilie	16
sardelle	3
büffelmozzarella	1

Smörgås	occ
brot	14
butter	15
dill	12
honig	8
kaviar	2
lachs	5
friséesalat	1

EI_w profits from low occurrence values of shared ingredients!

Making it visible



Combinatorics interlude

To describe a an ingredient relation by its source and target ingredient classes, we need

$k = 2$ picks from
 $n = 16$ ingredient classes.

That yields $\binom{n+k-1}{k}$ possible combinations assuming we order the picks.

Thus, with the above given values for n and k , we have

$\binom{17}{2} = 136$ possible combinations of source and target classes.

Aside:

For our sample collection, to describe an ingredient relation by its source and target ingredients, we need

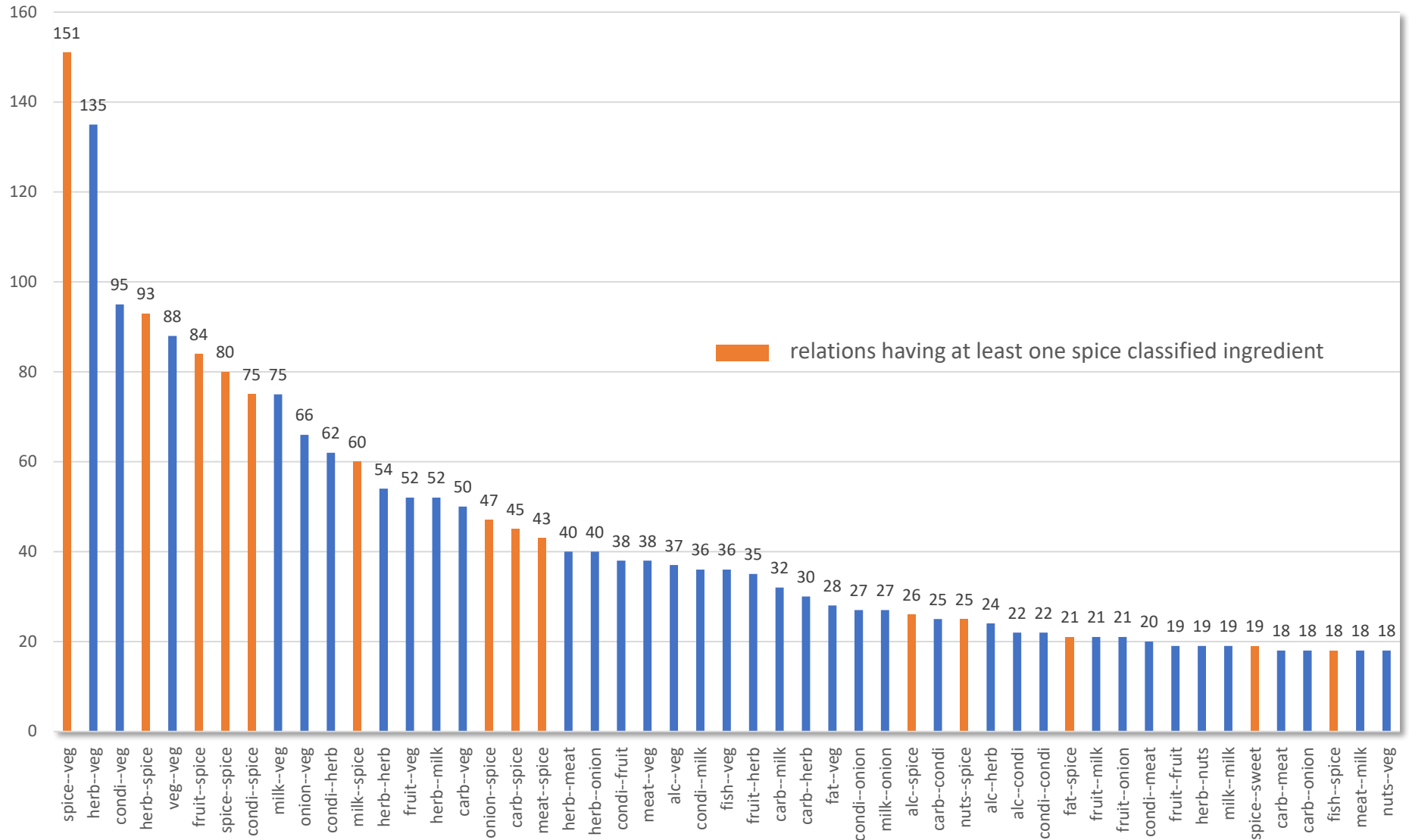
$k = 2$ picks from
 $n = 200$ ingredients.

That yields $\binom{n+k-1}{k}$ possible combinations assuming we order the picks.

Thus, with the above given values for n and k , we have

$\binom{201}{2} = 20100$ possible combinations of source and target ingredients.

Ingredient relations by ingredient classes



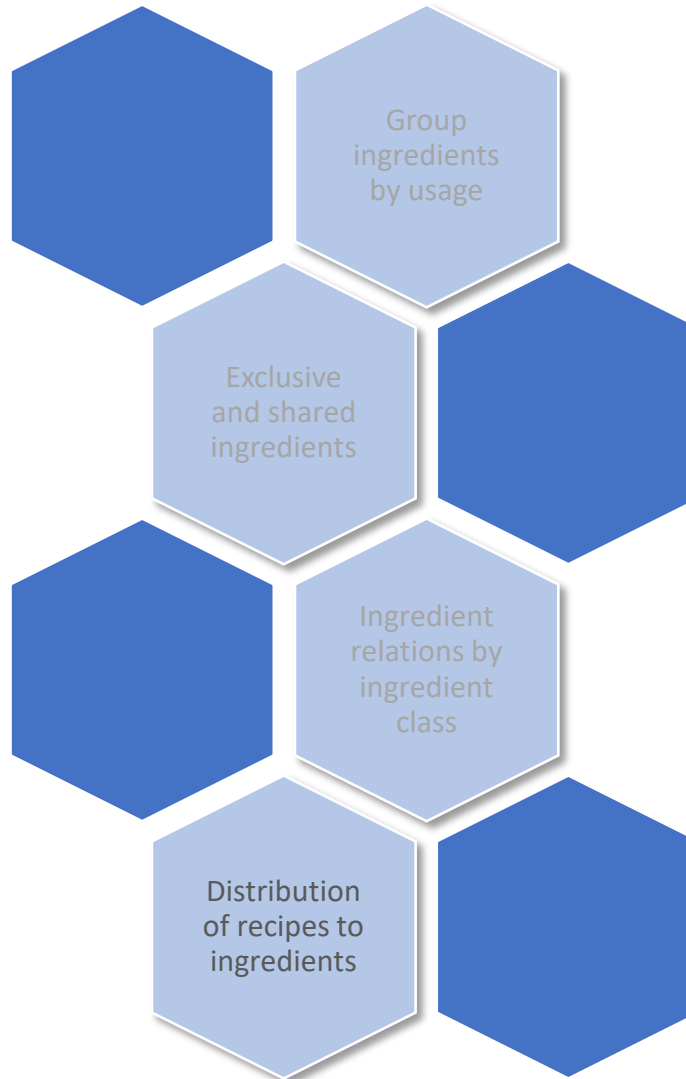
highest values only

Missing ingredient class relations

- Total of 126 relations; potentially 136 relations
- Unpopulated relations:

carb--etc
egg--egg
etc--etc
etc--fat
etc--fish
etc--nuts
etc--fruit
etc--spice
etc--sweet
nuts--nuts

Making it visible



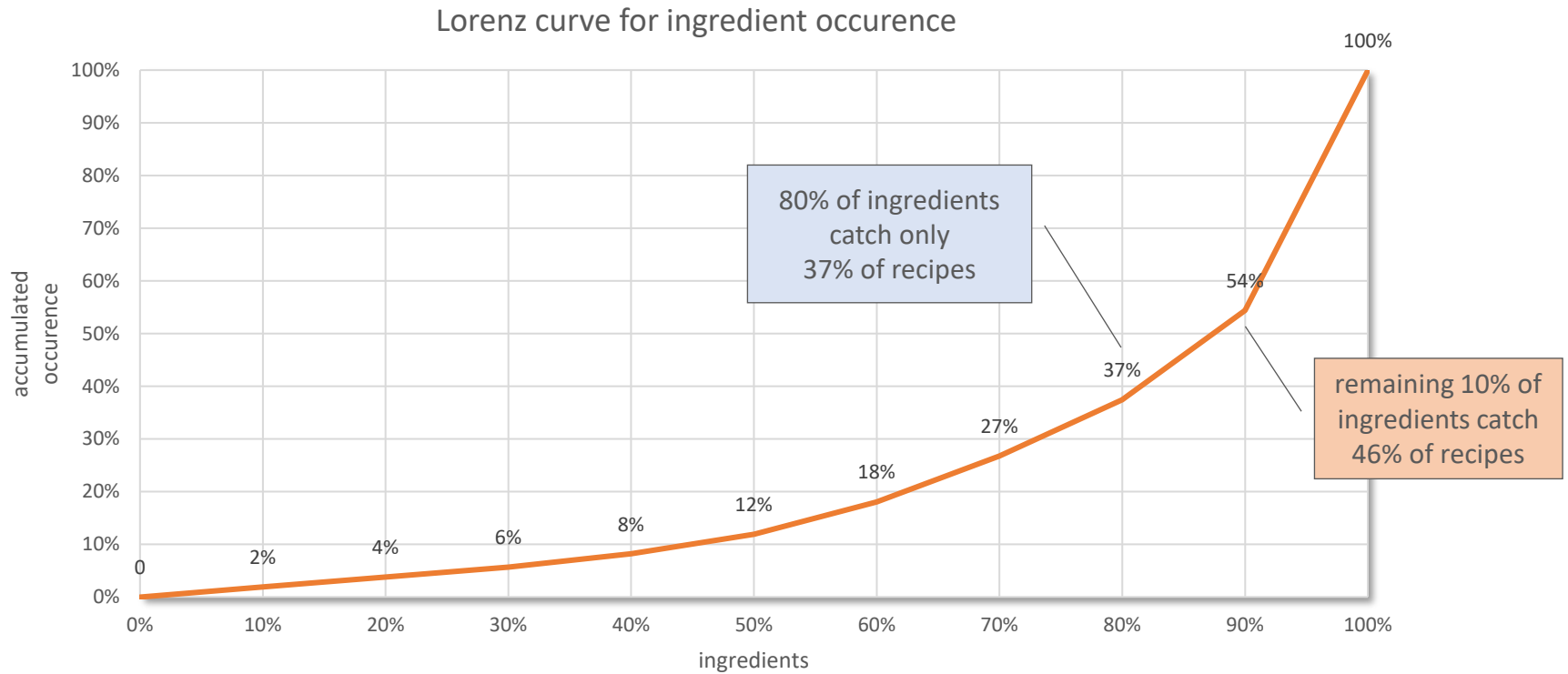
Idea

from: <https://ulis-culinaria.de/kulinarische-redewendungen/>

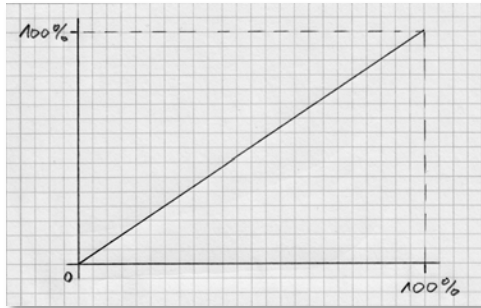


Ingredients catch recipes!

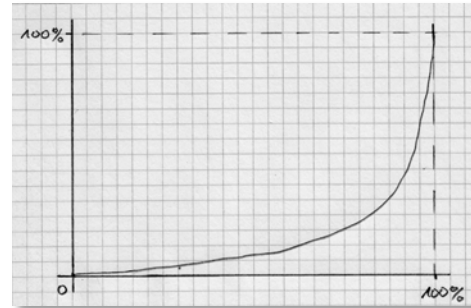
Lorenz curve and Gini coefficients



What the Lorenz curve can tell

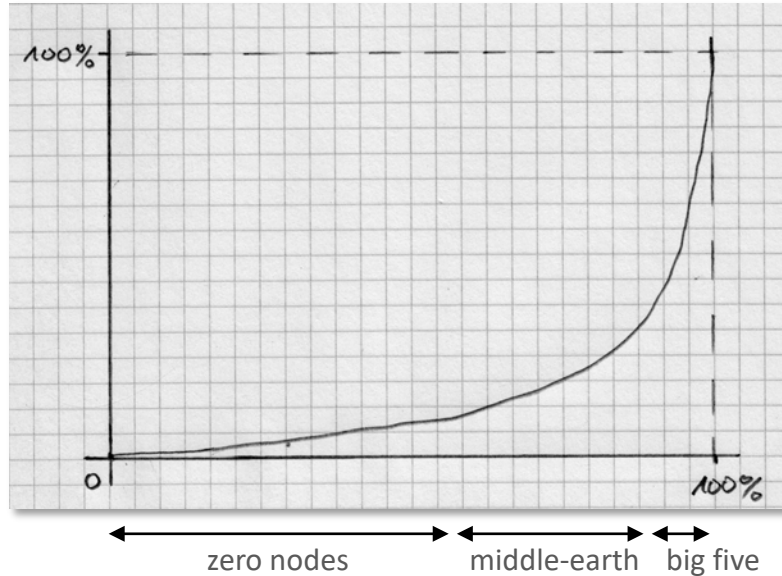


- perfect equality
- Gini coefficient = 0



- approaching perfect inequality
- Gini coefficient $\lesssim 1$, i.e. less than, but close to 1

Lorenz curve for ingredient graphs



When comparing culinary collections:

→ Larger Gini coefficient
signals more diverse collection.

- zero nodes curve gradient = 1
may completely disappear in favor of middle-earth
- middle-earth curve gradient > 1
may completely disappear in favor of zero nodes
- big five curve gradient $\gg 1$
always present (unless we assume a collection with less than 5 different ingredients)



Thank you!