UNDERSTANDING CUSTOMERS BETTER THROUGH NEURAL NETWORK EMBEDDINGS

Adam Hornsby
(adam.hornsby@dunnhumby.com)

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ABOUT ME

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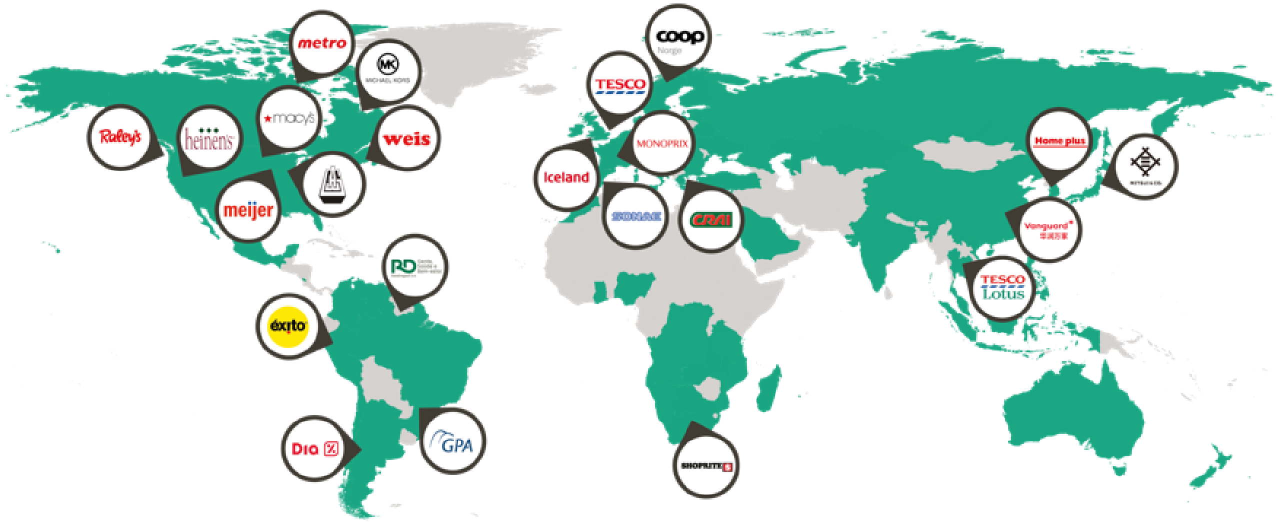
- Researching **consumer decision-making** through experiments, big-data and computational modelling

EXTENSIVE HERITAGE AND EXPERIENCE WORKING WITH RETAILERS AND BRANDS



Leading Global FMCG Companies

L'ORÉAL, Coca-Cola, General Mills, Kellogg's, Unilever, Reckitt Benckiser, Mondelēz International, Nestlé, Henkel, PEPSICO

Leading Consumer Brands

ESTĒE LAUDER, MICHAEL KORS, LUXOTTICA, GUESS BY MARCIANO, CHANEL, RALPH LAUREN, Levi's, Kenneth Cole, L'ORÉAL, COACH NEW YORK

Over 25 years experience

Using world-leading data and science to drive growth

72 retailers and **1,000+** brands

TODAY

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2. What are **embeddings**?
3. How can **2vec** algorithms help?
4. Conclusions

(Massive thanks to Josh Cooper for doing lots of the thinking in this presentation)

ITEM SIMILARITY

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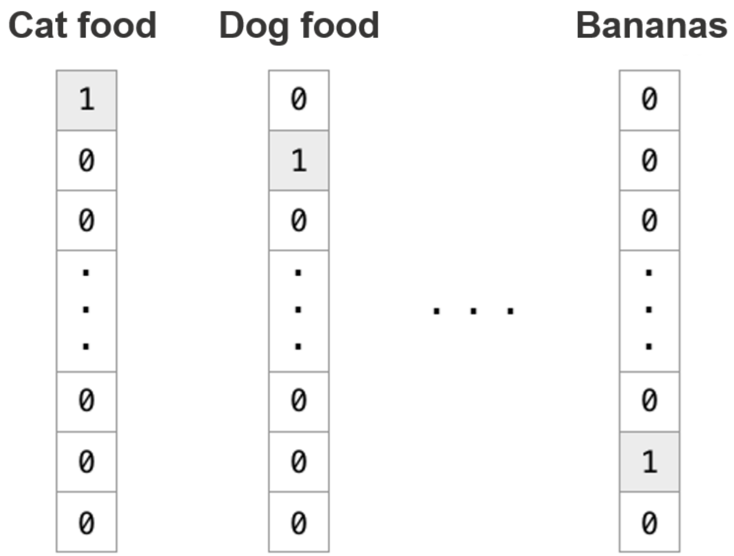
Solving similarity is a **huge goal for data scientists** working to improve; recommendations, ranging, pricing, assortment and more

TRADITIONAL METHODS DON'T HELP WITH SIMILARITY



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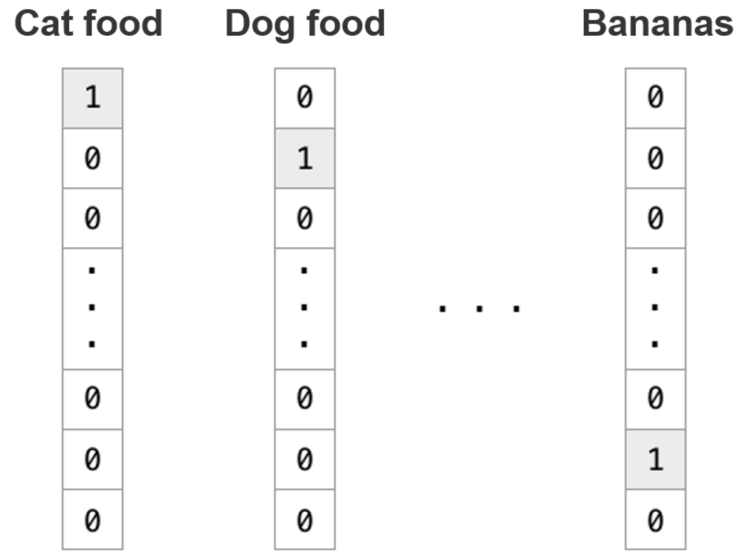

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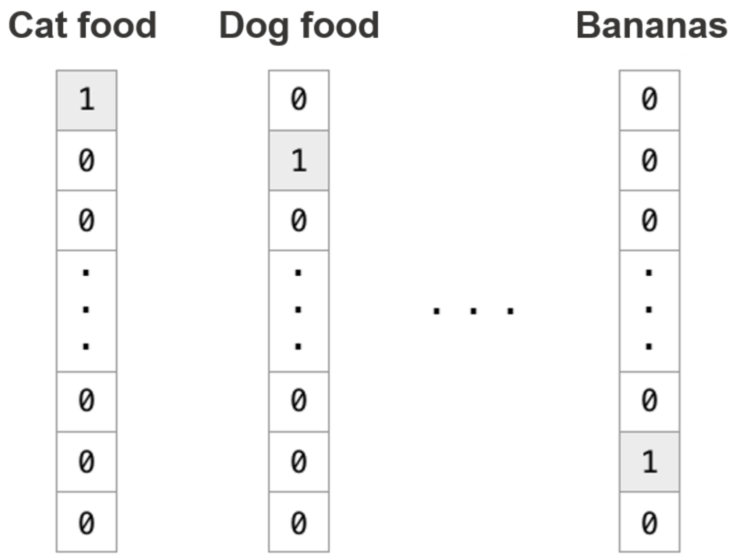

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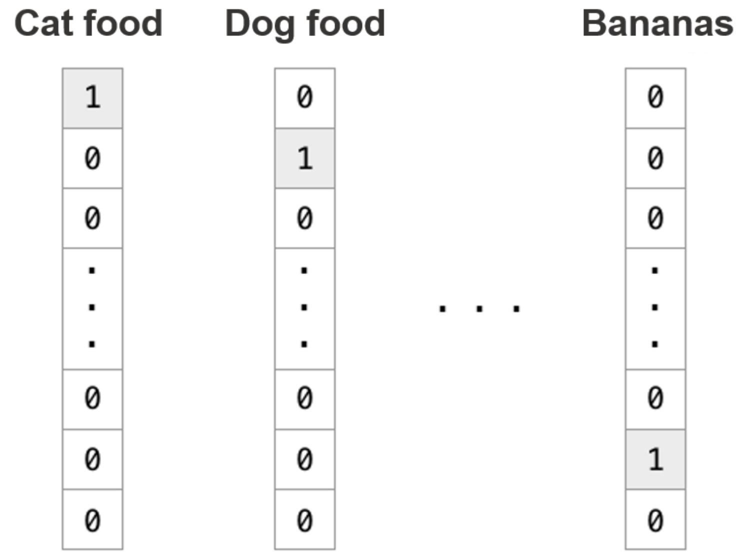

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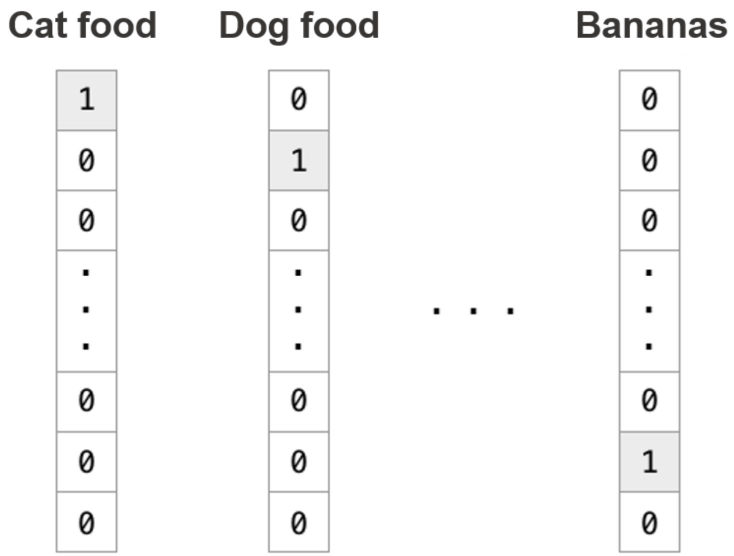

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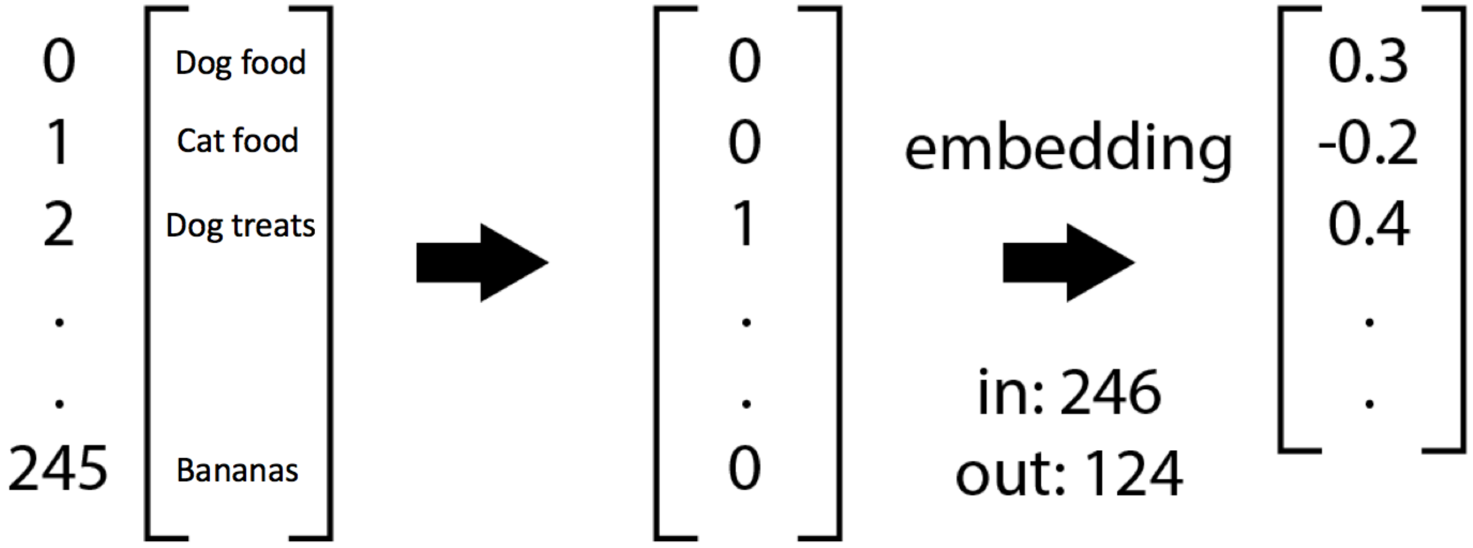
We need a way to represent these items using **dense** vectors

EMBEDDINGS

EMBEDDINGS ARE DENSE REPRESENTATIONS

for the product 'Dog food'



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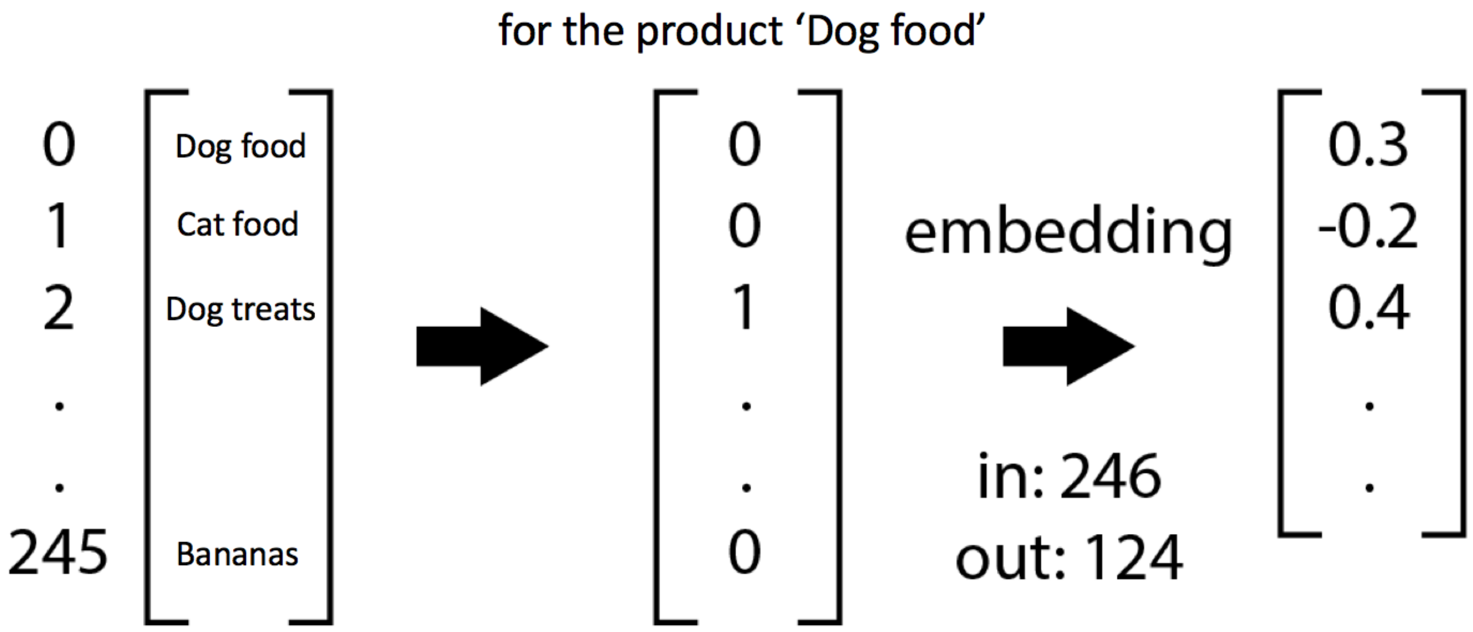

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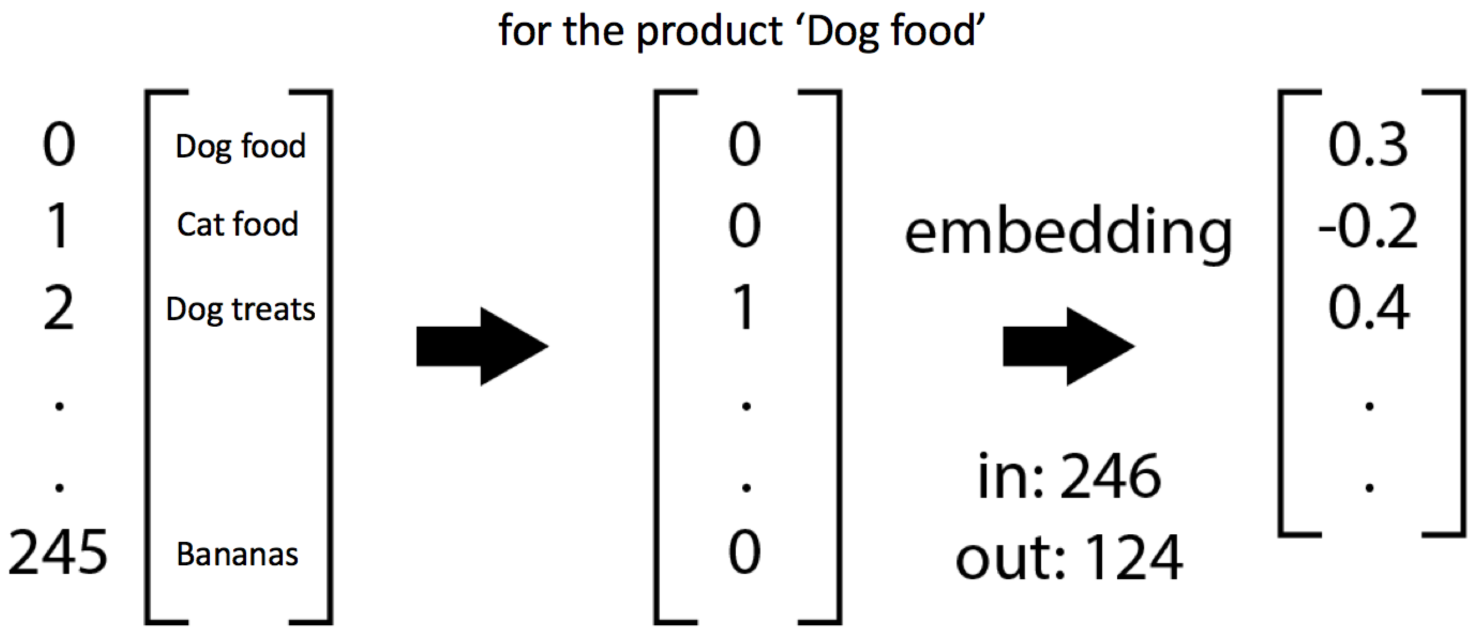

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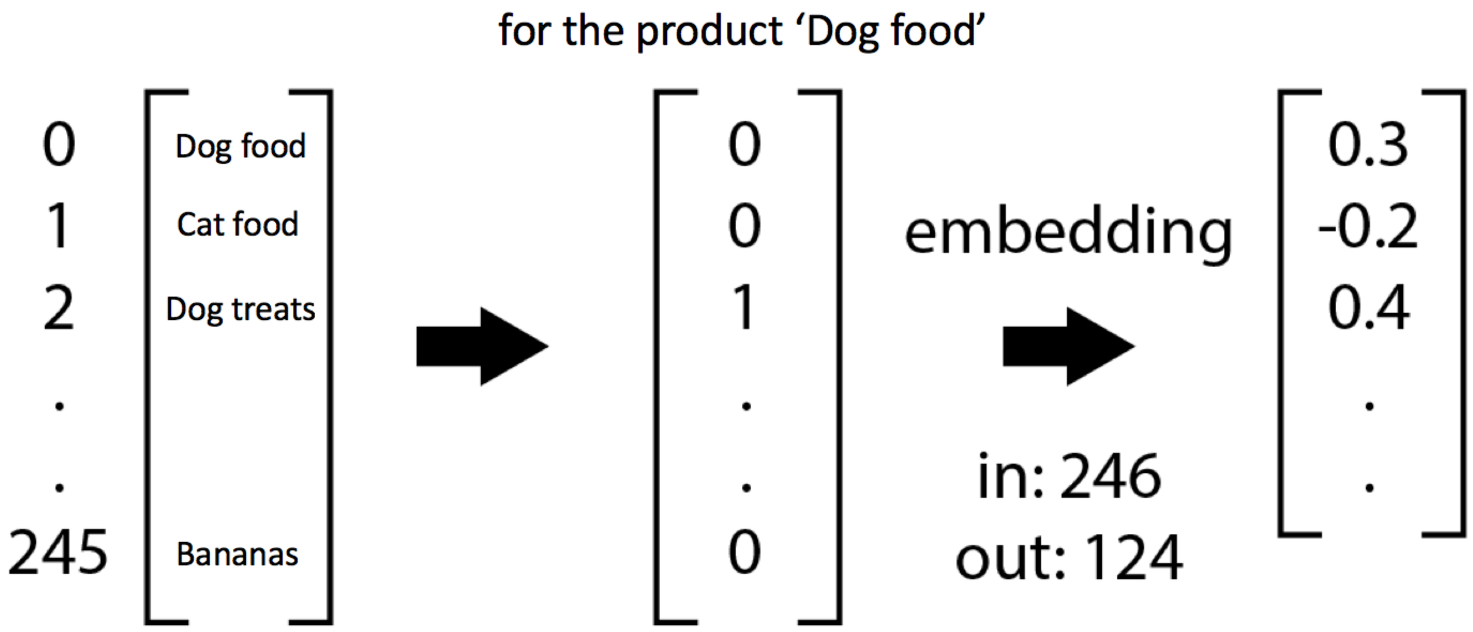

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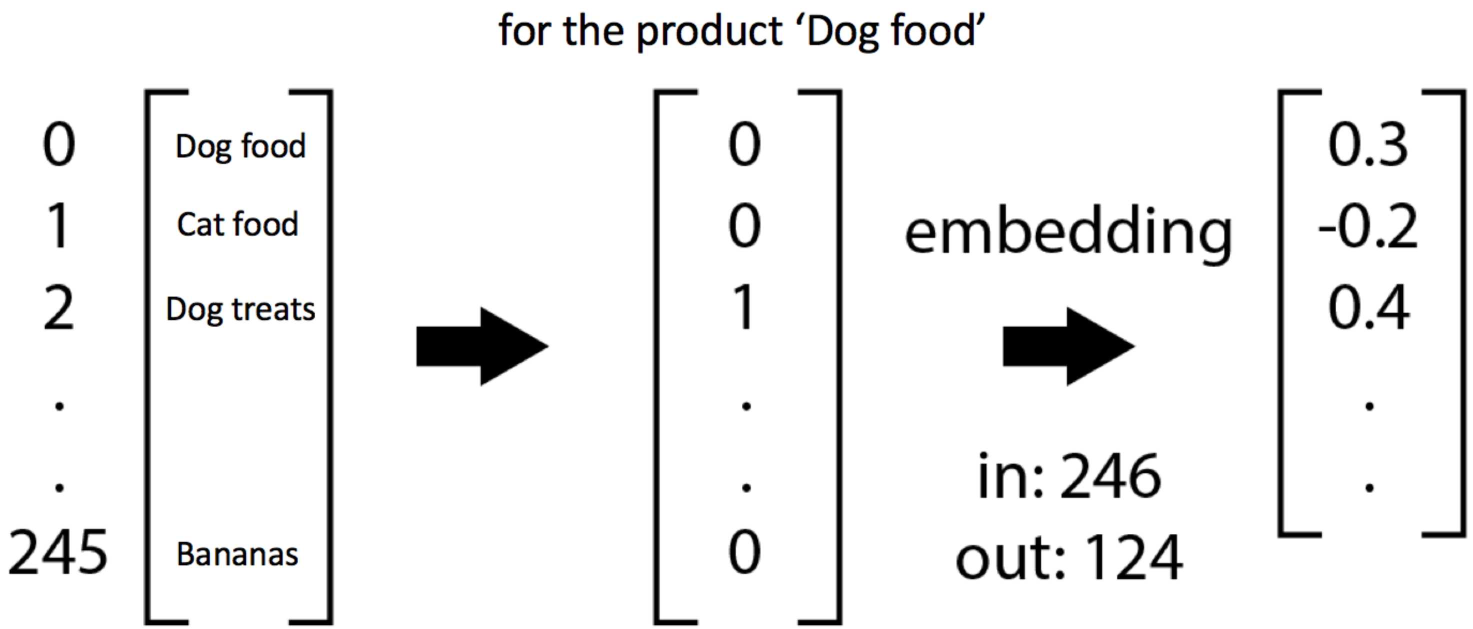

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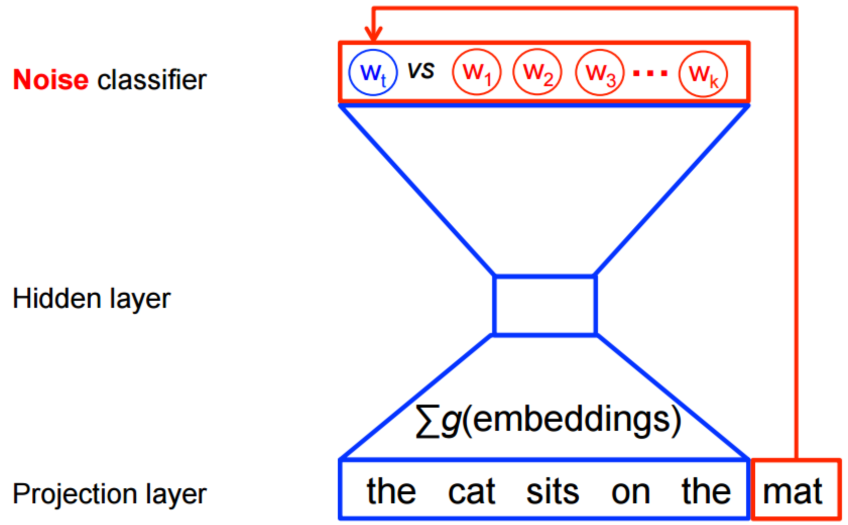
When learned well, produce **similar vectors for similar items** (e.g. cats vs. dogs)

*2VEC ALGORITHMS



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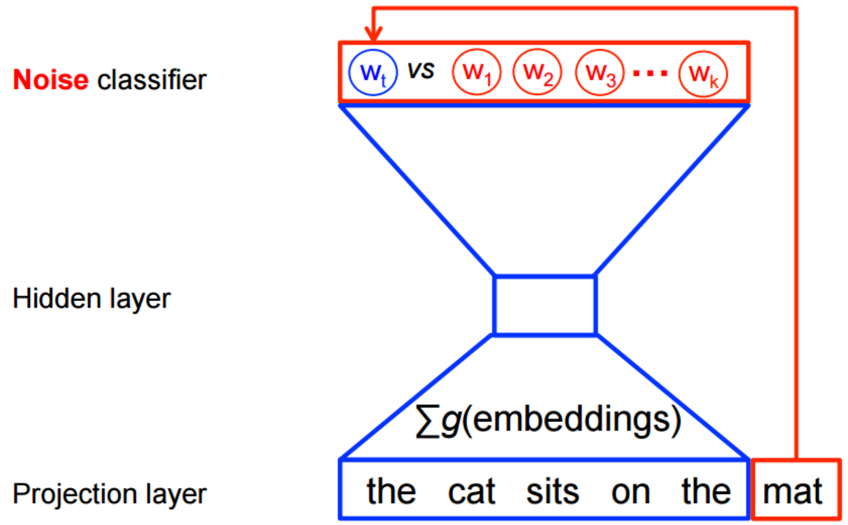

A set of **unsupervised learning** algorithms that learn vector embeddings (Mikolov et al.)

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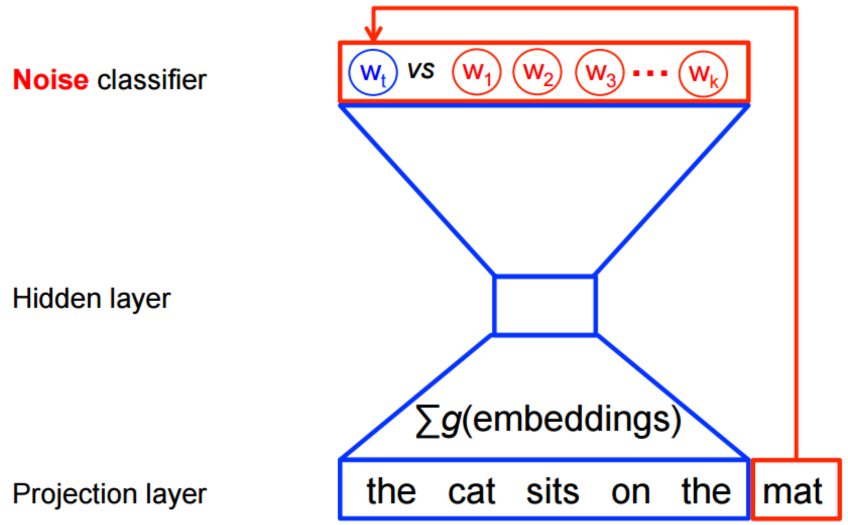

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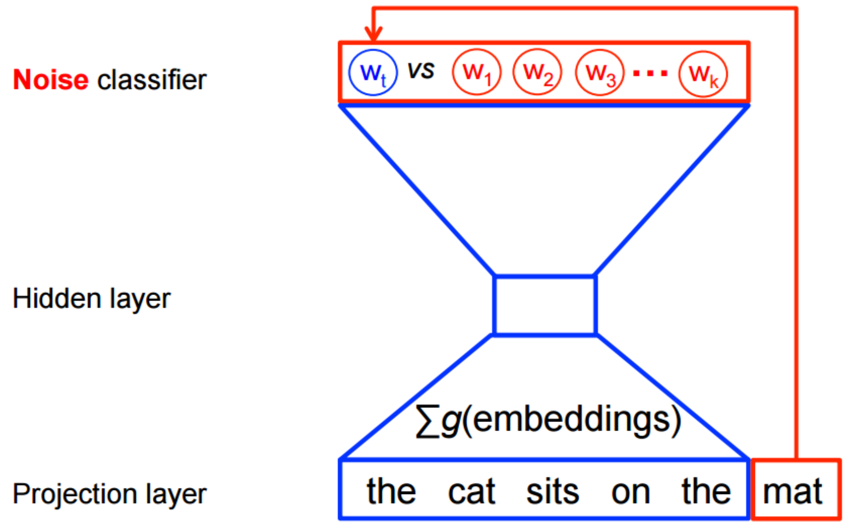

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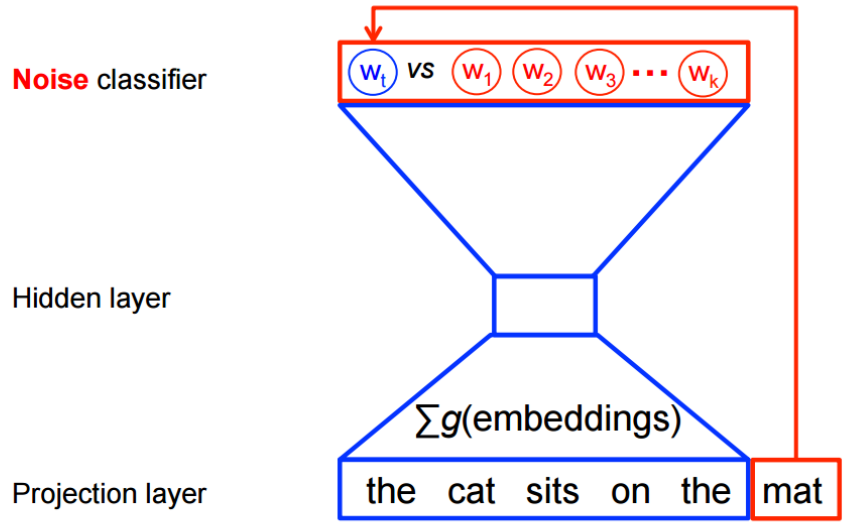

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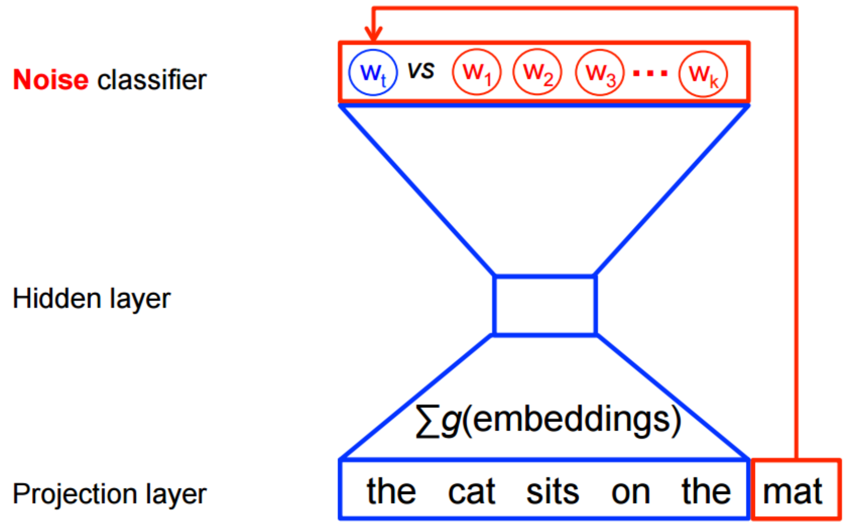

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Create **lots of little classification problems** (e.g. use vector of one item to predict next item in document, then backprop)
Typically **very fast to train** and scale well to large data

SENTENCES VS. BASKETS

"I love Rice Crispies, Wheat Thins and peanut butter"

=

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NLP algorithms (like doc2vec) assume that you have **words (i.e. items) and sentences (i.e. documents)**

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NLP algorithms (like doc2vec) assume that you have **words (i.e. items) and sentences (i.e. documents)**

Products are analogous to words and **baskets/customers** are analogous to sentences (e.g. A basket is represented with product codes)

This data is a **neat place to test NLP algorithms** (e.g. no order, "stop words" and arguably more natural)

THE MODEL

THE MODELLING PROBLEM

dunnhumby | SOURCE FILES

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Aim: Understand whether doc2vec can learn **useful** vector representations of products and baskets

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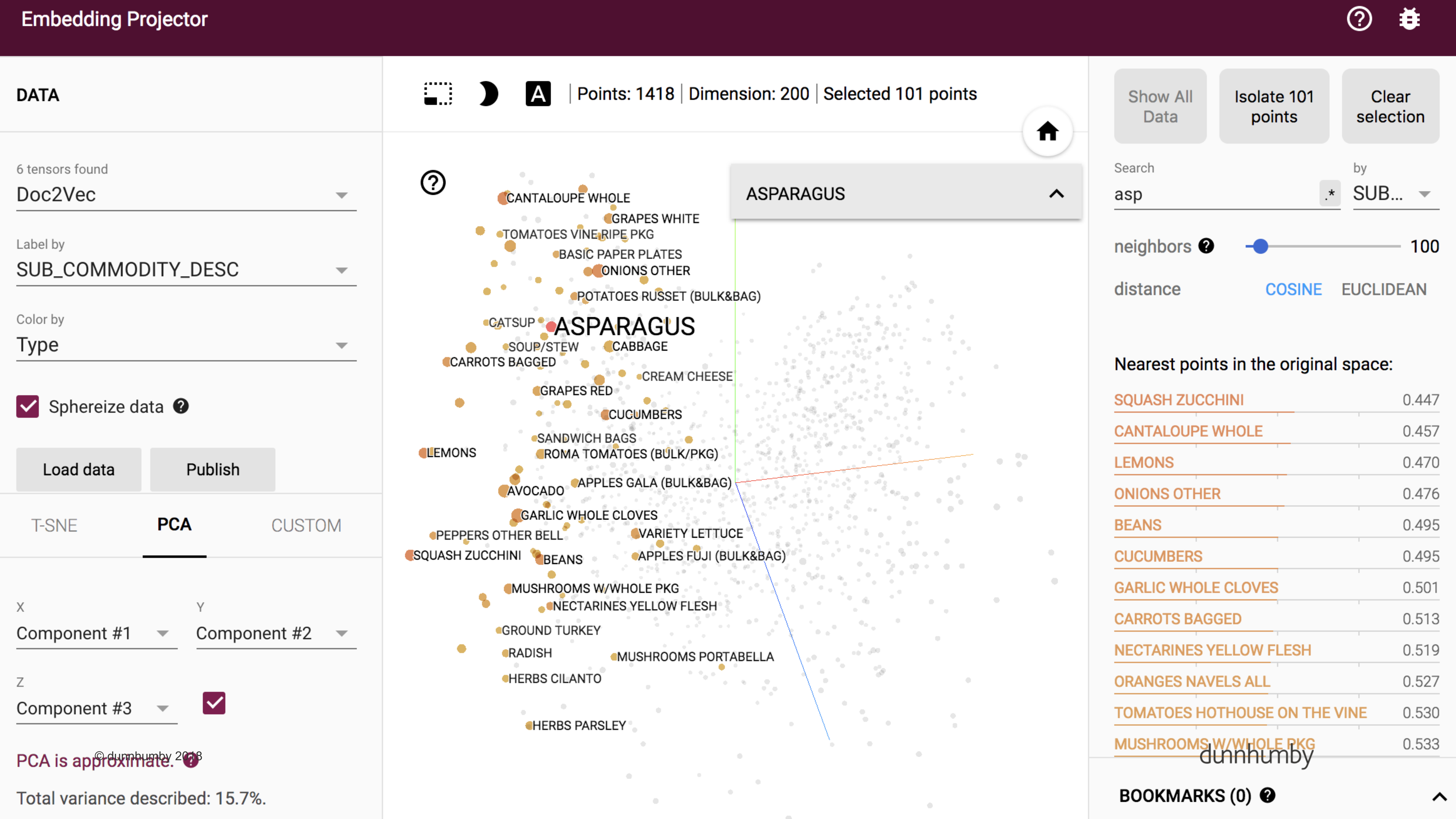
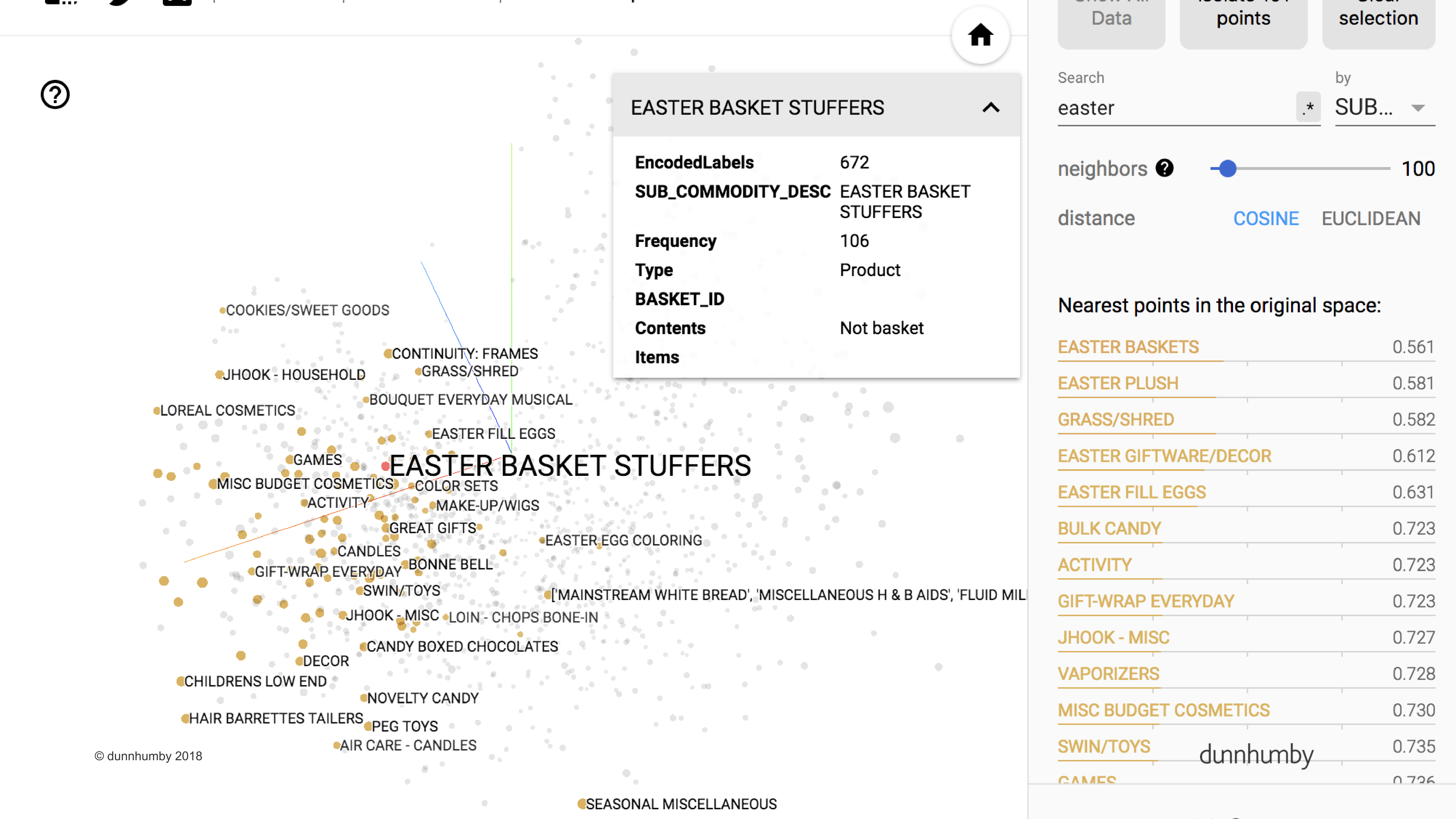
Model solutions evaluated using Tensorflow's amazing Embedding Projector

EVALUATION


Embedding Projector
DATA
6 tensors found
Doc2Vec
Label by
SUB_COMMODITY_DESC
Color by
Type
Sphereize data
Load data
Publish
T-SNE
PCA
CUSTOM
X
Component #1
Y
Component #2
Z
Component #3
PCA is approximate.
Total variance described: 15.7%.
Points: 1418 | Dimension: 200 | Selected 101 points
ASPARAGUS
CANTALOUPE WHOLE
GRAPES WHITE
TOMATOES VINE RIPE PKG
BASIC PAPER PLATES
ONIONS OTHER
POTATOES RUSSET (BULK&BAG)
CATSUP
SOUP/STEW
CABBAGE
CARROTS BAGGED
CREAM CHEESE
GRAPES RED
CUCUMBERS
SANDWICH BAGS
LEMONS
ROMA TOMATOES (BULK/PKG)
APPLES GALA (BULK&BAG)
AVOCADO
GARLIC WHOLE CLOVES
PEPPERS OTHER BELL
VARIETY LETTUCE
SQUASH ZUCCHINI
BEANS
APPLES FUJI (BULK&BAG)
MUSHROOMS W/WHOLE PKG
NECTARINES YELLOW FLESH
GROUND TURKEY
RADISH
MUSHROOMS PORTABELLA
HERBS CILANTO
HERBS PARSLEY
Show All Data
Isolate 101 points
Clear selection
Search
asp
by
SUB...
neighbors
100
distance
COSINE
EUCLIDEAN
Nearest points in the original space:
SQUASH ZUCCHINI 0.447
CANTALOUPE WHOLE 0.457
LEMONS 0.470
ONIONS OTHER 0.476
BEANS 0.495
CUCUMBERS 0.495
GARLIC WHOLE CLOVES 0.501
CARROTS BAGGED 0.513
NECTARINES YELLOW FLESH 0.519
ORANGES NAVELS ALL 0.527
TOMATOES HOTHOUSE ON THE VINE 0.530
MUSHROOMS W/WHOLE PKG 0.533
BOOKMARKS (0)


EASTER BASKET STUFFERS
EncodedLabels 672
SUB_COMMODITY_DESC EASTER BASKET STUFFERS
Frequency 106
Type Product
BASKET_ID
Contents Not basket
Items
Data
points
selection
Search
easter
by
SUB...
neighbors
100
distance
COSINE
EUCLIDEAN
Nearest points in the original space:
EASTER BASKETS 0.561
EASTER PLUSH 0.581
GRASS/SHRED 0.582
EASTER GIFTWARE/DECOR 0.612
EASTER FILL EGGS 0.631
BULK CANDY 0.723
ACTIVITY 0.723
GIFT-WRAP EVERYDAY 0.723
JHOOK - MISC 0.727
VAPORIZERS 0.728
MISC BUDGET COSMETICS 0.730
SWIN/TOYS 0.735
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COOKIES/SWEET GOODS
CONTINUITY: FRAMES
JHOOK - HOUSEHOLD
GRASS/SHRED
BOUQUET EVERYDAY MUSICAL
LOREAL COSMETICS
EASTER FILL EGGS
GAMES
EASTER BASKET STUFFERS
MISC BUDGET COSMETICS
COLOR SETS
ACTIVITY
MAKE-UP/WIGS
GREAT GIFTS
EASTER EGG COLORING
CANDLES
BONNE BELL
GIFT-WRAP EVERYDAY
SWIN/TOYS
['MAINSTREAM WHITE BREAD', 'MISCELLANEOUS H & B AIDS', 'FLUID MIL
JHOOK - MISC
LOIN - CHOPS BONE-IN
CANDY BOXED CHOCOLATES
DECOR
CHILDRENS LOW END
NOVELTY CANDY
HAIR BARRETTES TAILERS
PEG TOYS
AIR CARE - CANDLES
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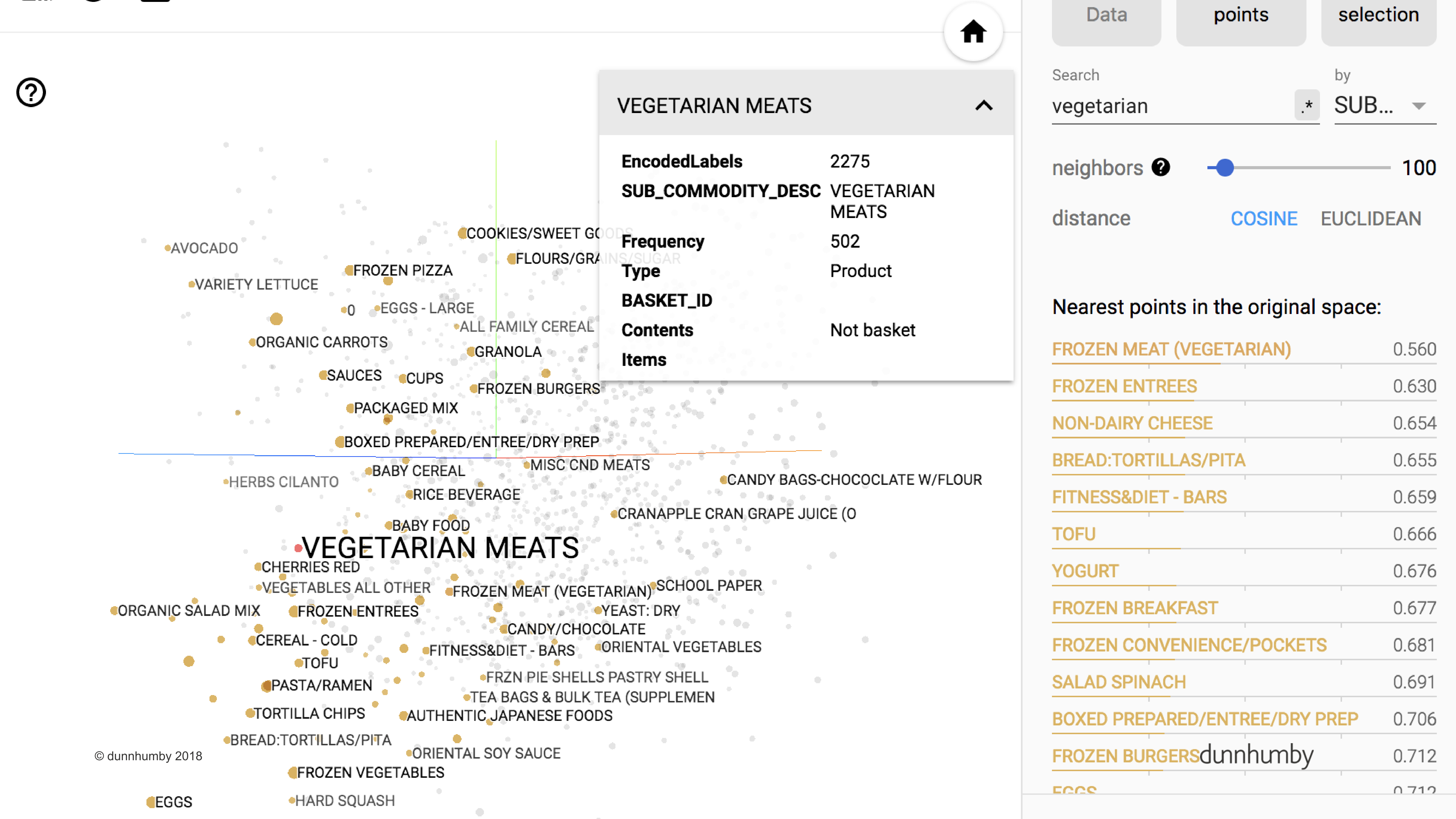
SEASONAL MISCELLANEOUS


Data
points
selection
Search
by
vegetarian
SUB...
neighbors
100
distance
COSINE
EUCLIDEAN
Nearest points in the original space:
FROZEN MEAT (VEGETARIAN) 0.560
FROZEN ENTREES 0.630
NON-DAIRY CHEESE 0.654
BREAD:TORTILLAS/PITA 0.655
FITNESS&DIET - BARS 0.659
TOFU 0.666
YOGURT 0.676
FROZEN BREAKFAST 0.677
FROZEN CONVENIENCE/POCKETS 0.681
SALAD SPINACH 0.691
BOXED PREPARED/ENTREE/DRY PREP 0.706
FROZEN BURGERS 0.712
VEGETARIAN MEATS
EncodedLabels 2275
SUB_COMMODITY_DESC VEGETARIAN MEATS
Frequency 502
Type Product
BASKET_ID
Contents Not basket
Items
AVOCADO
VARIETY LETTUCE
FROZEN PIZZA
EGGS - LARGE
ALL FAMILY CEREAL
ORGANIC CARROTS
GRANOLA
SAUCES
CUPS
FROZEN BURGERS
PACKAGED MIX
BOXED PREPARED/ENTREE/DRY PREP
BABY CEREAL
MISC CND MEATS
HERBS CILANTO
RICE BEVERAGE
CANDY BAGS-CHOCOCLATE W/FLOUR
CRANAPPLE CRAN GRAPE JUICE (O
BABY FOOD
VEGETARIAN MEATS
CHERRIES RED
VEGETABLES ALL OTHER
FROZEN MEAT (VEGETARIAN)
SCHOOL PAPER
ORGANIC SALAD MIX
FROZEN ENTREES
YEAST: DRY
CANDY/CHOCOLATE
CEREAL - COLD
FITNESS&DIET - BARS
ORIENTAL VEGETABLES
TOFU
FRZN PIE SHELLS PASTRY SHELL
PASTA/RAMEN
TEA BAGS & BULK TEA (SUPPLEMEN
TORTILLA CHIPS
AUTHENTIC JAPANESE FOODS
BREAD:TORTILLAS/PITA
ORIENTAL SOY SAUCE
FROZEN VEGETABLES
EGGS
HARD SQUASH
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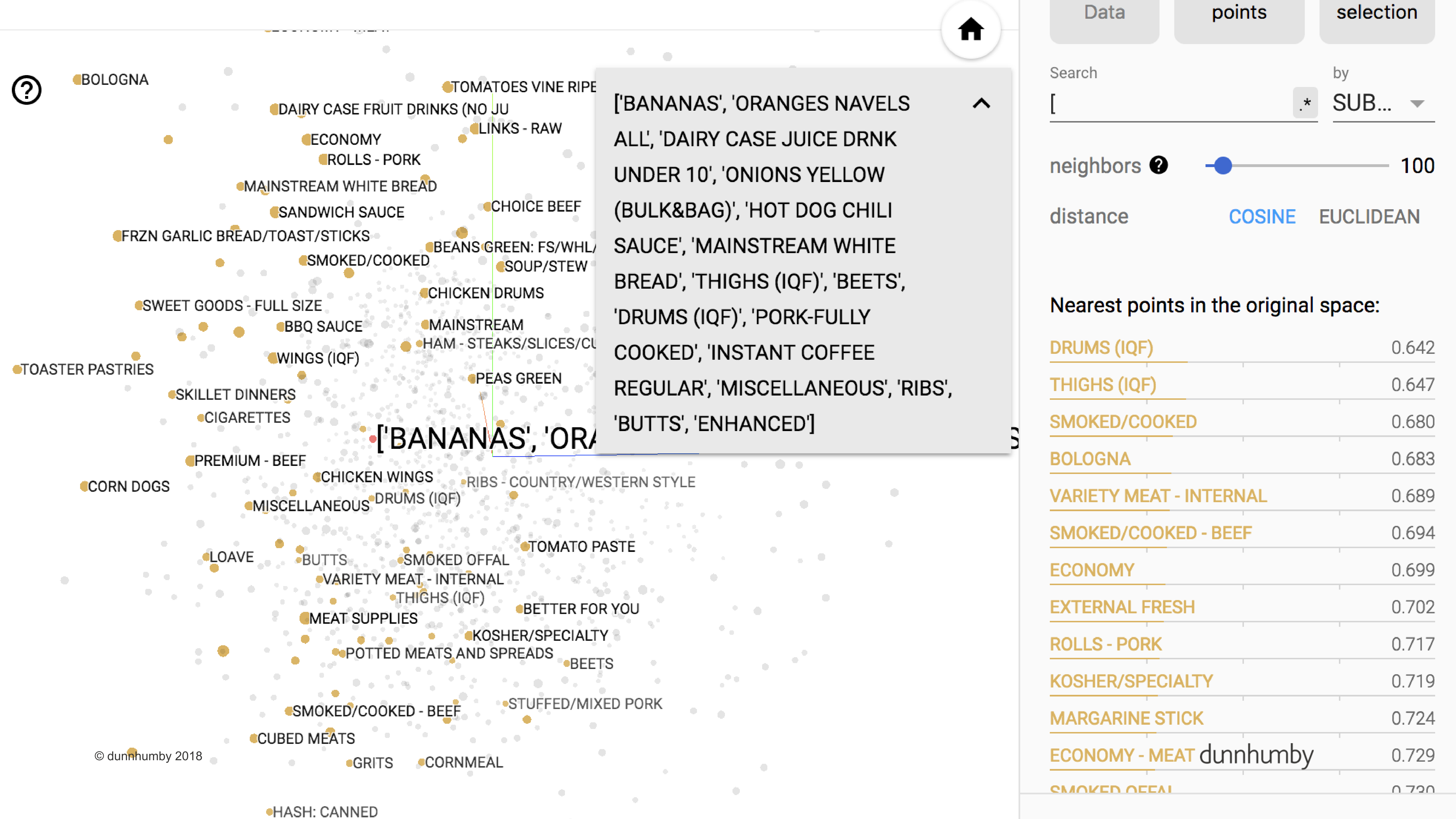
Data
points
selection
Search
by
SUB...
neighbors
100
distance
COSINE
EUCLIDEAN
Nearest points in the original space:
DRUMS (IQF) 0.642
THIGHS (IQF) 0.647
SMOKED/COOKED 0.680
BOLOGNA 0.683
VARIETY MEAT - INTERNAL 0.689
SMOKED/COOKED - BEEF 0.694
ECONOMY 0.699
EXTERNAL FRESH 0.702
ROLLS - PORK 0.717
KOSHER/SPECIALTY 0.719
MARGARINE STICK 0.724
ECONOMY - MEAT 0.729
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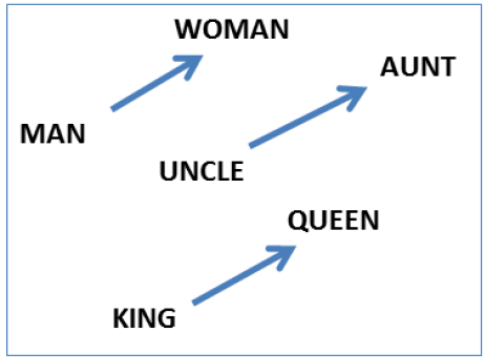
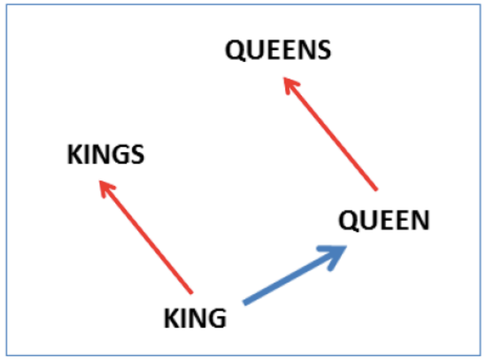
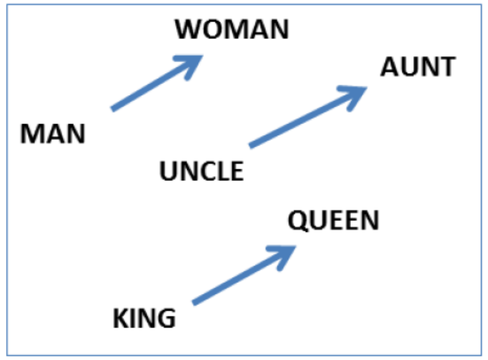
['BANANAS', 'ORANGES NAVELS ALL', 'DAIRY CASE JUICE DRNK UNDER 10', 'ONIONS YELLOW (BULK&BAG)', 'HOT DOG CHILI SAUCE', 'MAINSTREAM WHITE SAUCE', 'MAINSTREAM WHITE BREAD', 'THIGHS (IQF)', 'BEETS', 'DRUMS (IQF)', 'PORK-FULLY COOKED', 'INSTANT COFFEE REGULAR', 'MISCELLANEOUS', 'RIBS', 'BUTTS', 'ENHANCED']
BOLOGNA
TOMATOES VINE RIPE
DAIRY CASE FRUIT DRINKS (NO JU
LINKS - RAW
ECONOMY
ROLLS - PORK
MAINSTREAM WHITE BREAD
CHOICE BEEF
SANDWICH SAUCE
FRZN GARLIC BREAD/TOAST/STICKS
BEANS GREEN: FS/WHL/
SMOKED/COOKED
SOUP/STEW
CHICKEN DRUMS
SWEET GOODS - FULL SIZE
BBQ SAUCE
MAINSTREAM
HAM - STEAKS/SLICES/CU
WINGS (IQF)
TOASTER PASTRIES
PEAS GREEN
SKILLET DINNERS
CIGARETTES
['BANANAS', 'ORA
PREMIUM - BEEF
CHICKEN WINGS
RIBS - COUNTRY/WESTERN STYLE
CORN DOGS
MISCELLANEOUS
DRUMS (IQF)
TOMATO PASTE
LOAVE
BUTTS
SMOKED OFFAL
VARIETY MEAT - INTERNAL
THIGHS (IQF)
BETTER FOR YOU
MEAT SUPPLIES
KOSHER/SPECIALTY
POTTED MEATS AND SPREADS
BEETS
SMOKED/COOKED - BEEF
STUFFED/MIXED PORK
CUBED MEATS
© dunnhumby 2018
GRITS
CORNMEAL
HASH: CANNED

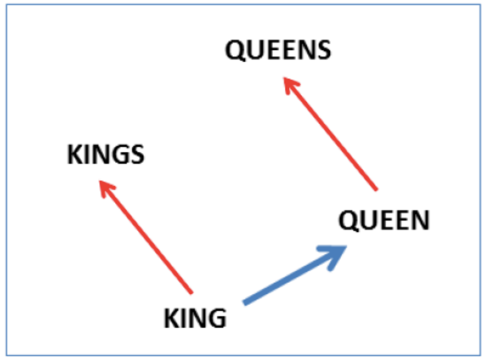
ANALOGICAL REASONING





ANALOGICAL REASONING





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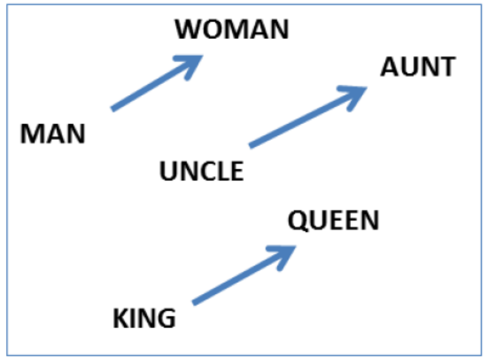

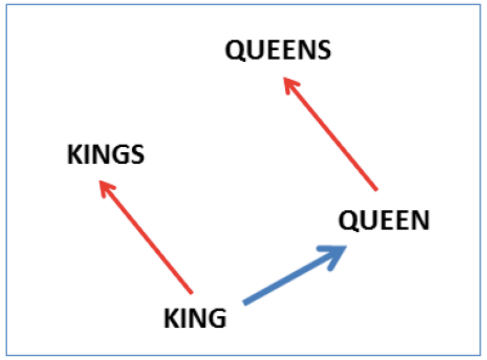

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$$King - Man + Woman = y$$

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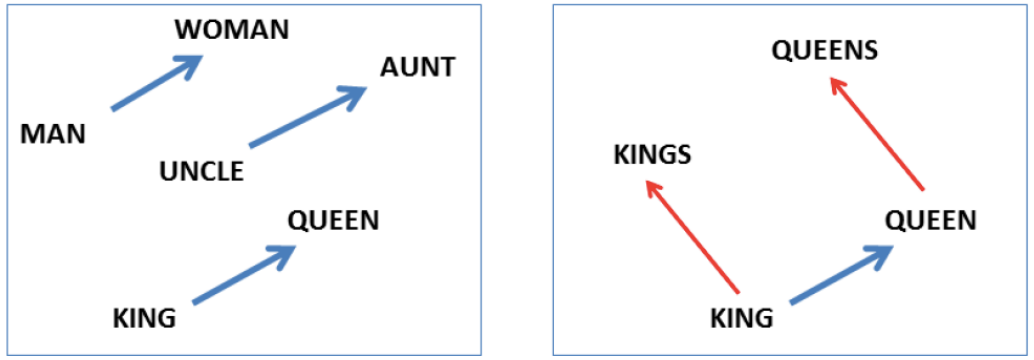

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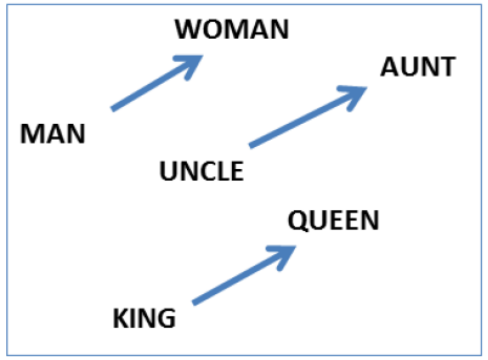

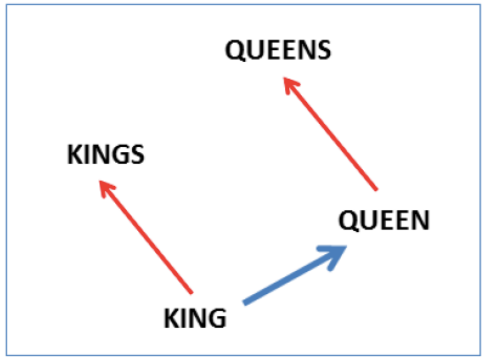

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What would be the equivalent using **product embeddings**?

IDENTIFYING CHEAPER ALTERNATIVES

Premium Meat - Premium + Economy = ?

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Rank	Product description	Cosine similarity
1	Economy meat	0.542439
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Suggests that there is a **"price sensitivity"** direction within the space

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Suggests there are **"frozen"** and **"vegetarian"** directions within the embedding space

CONCLUSIONS

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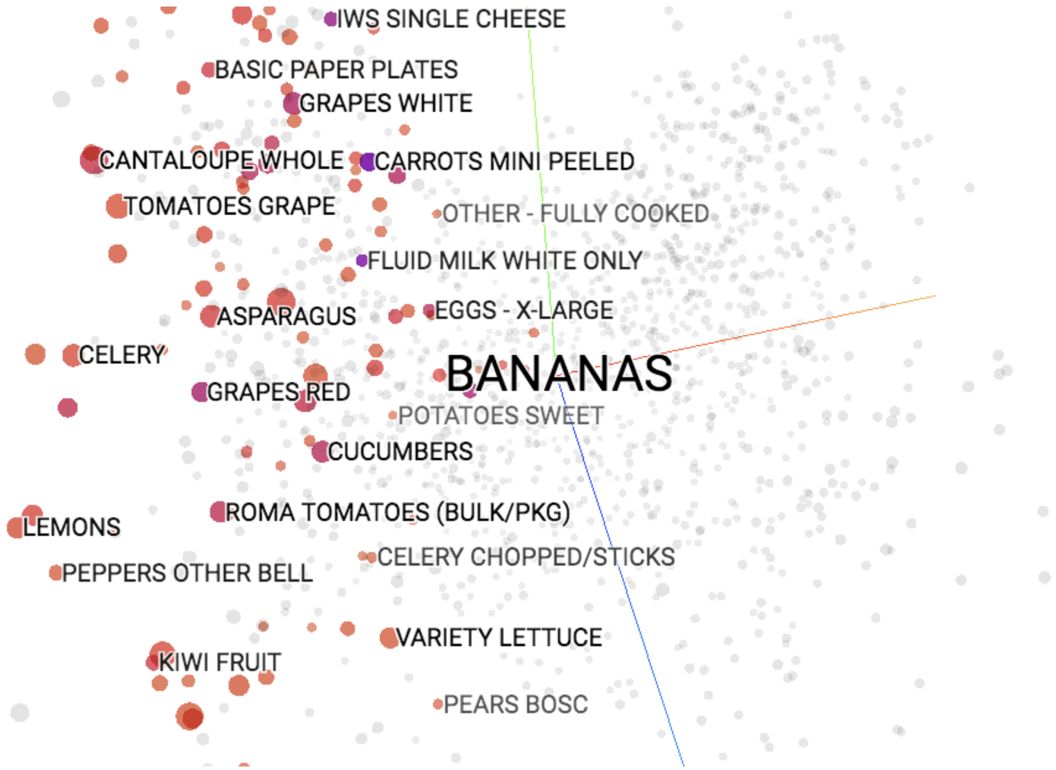

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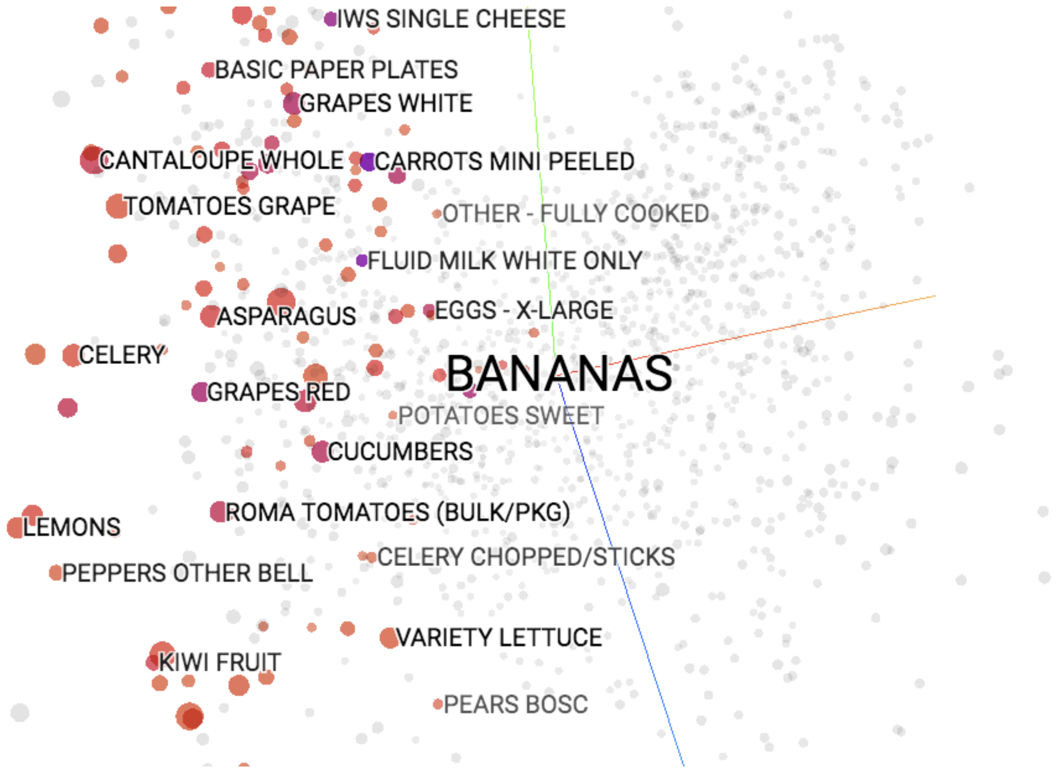

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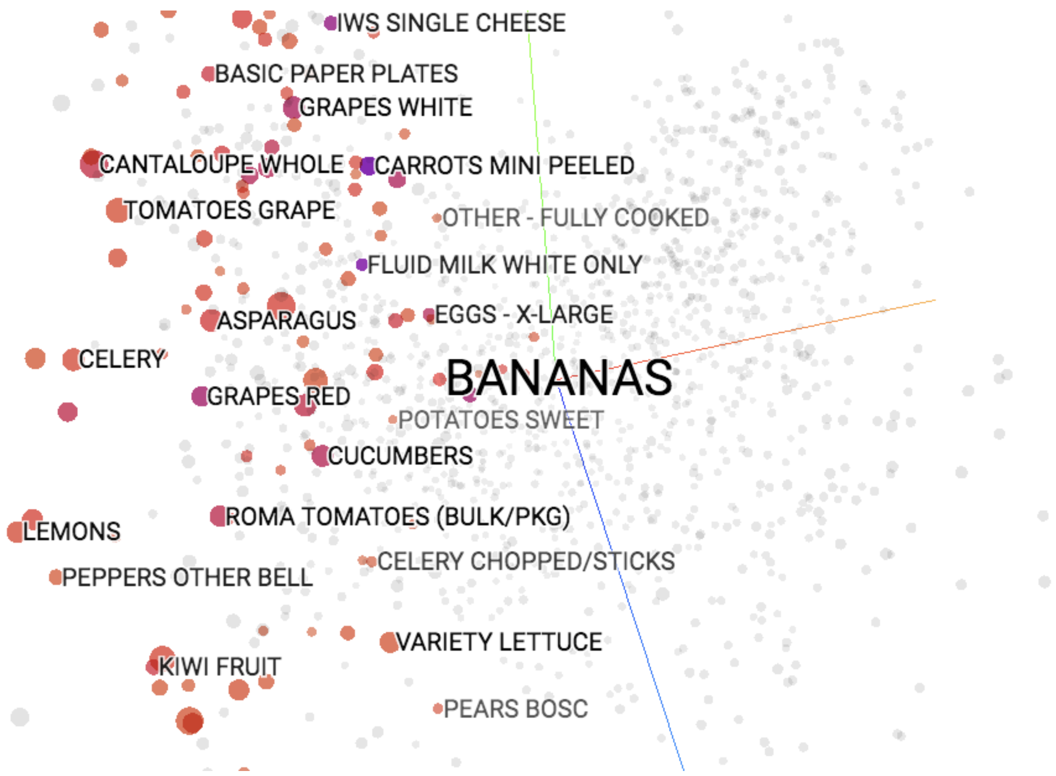

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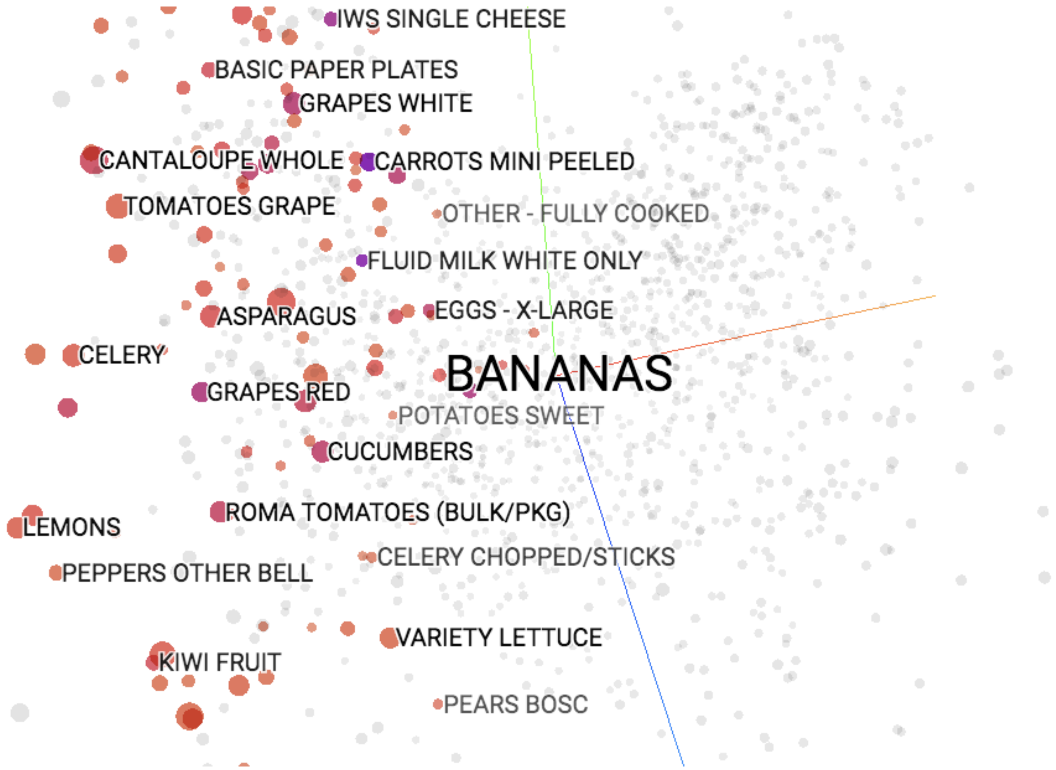

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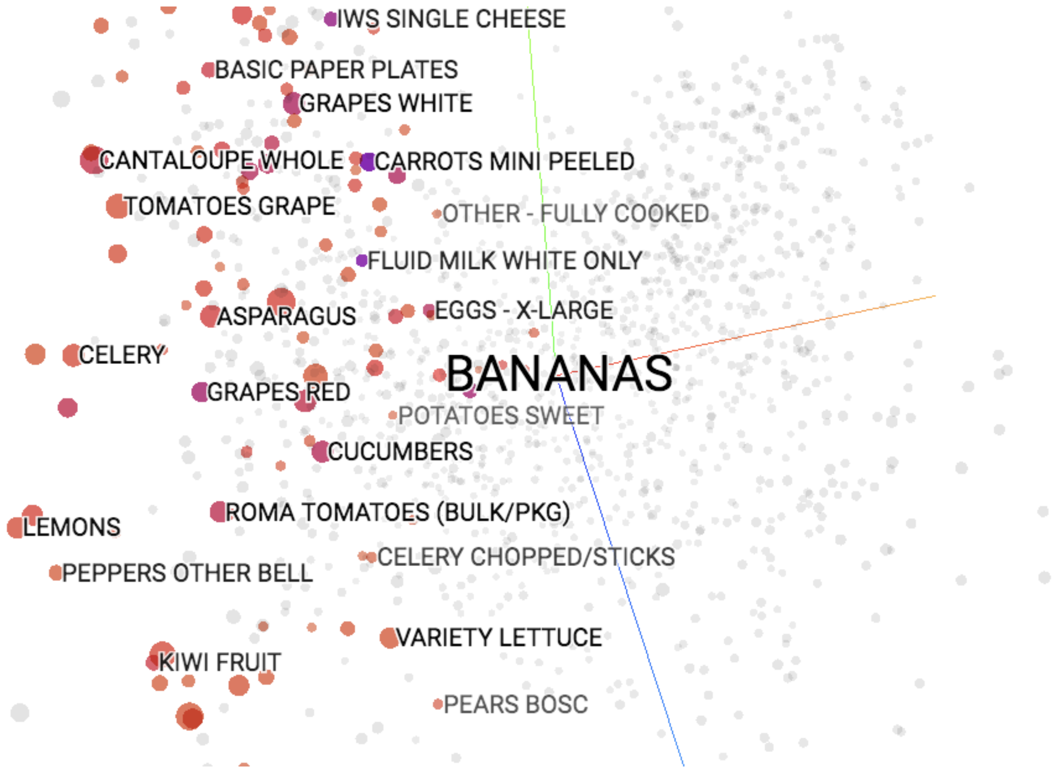

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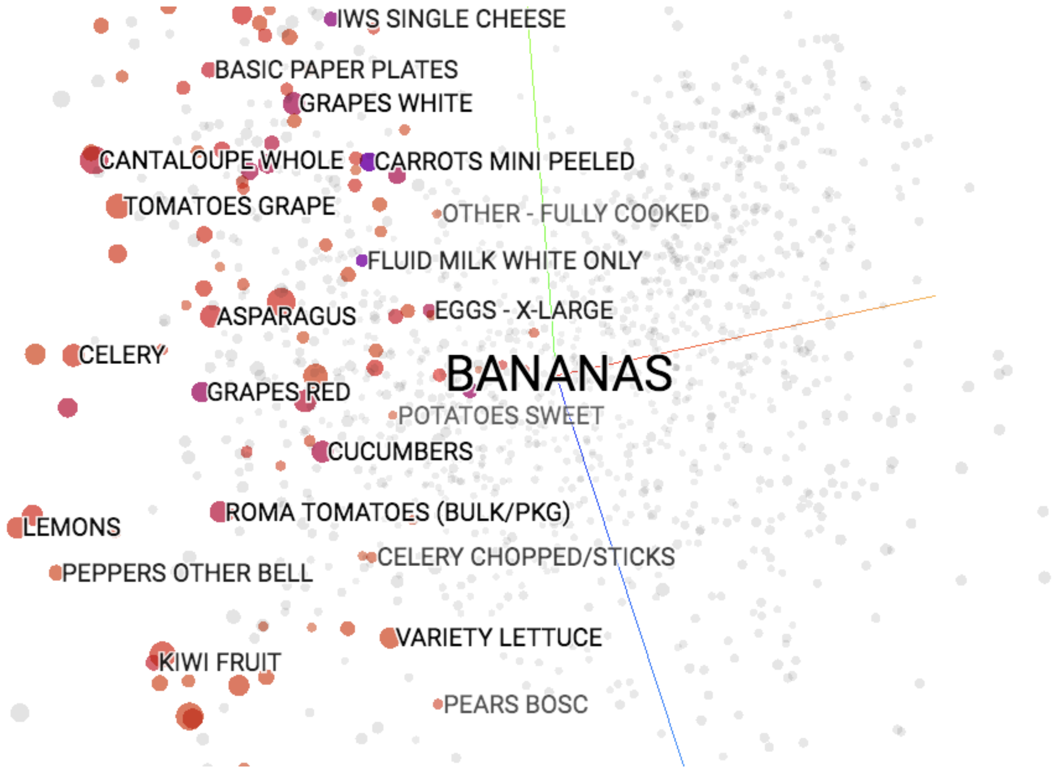

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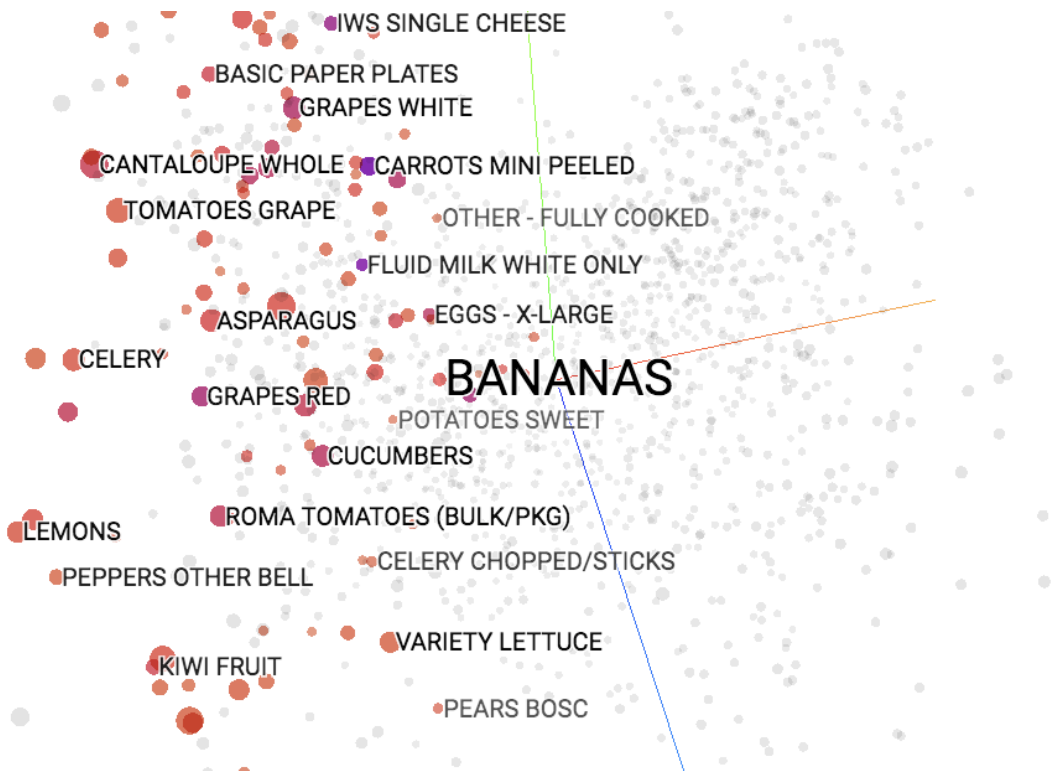

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- Need some more **automated** ways of **evaluating** the model

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Global deployment of model in collaboration with partners

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A **significant leap forward** in the endeavour to describe **similarity**

THANK YOU

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