# Non-Negative Matrix Factorization

An Introduction to Topic Discovery and Latent Features



#### Objectives

- Describe to your friends what NMF is
  - "Unbaking cakes" into their original ingredients
  - Feature space reduction, i.e. describe the data with less features
    - Not just a subset of original features!
  - Find "latent topics" based on the many cake features
- Know applications for NMF and similar models
  - Example: Genre discovery from user/movie ratings data
  - Recommender systems [Saving this for Thursday]
- Use Alternating Least Squares or Gradient Descent to "unbake the cake"
- Lay down the fundamental concepts we'll use again in Principal Component Analysis (PCA) & Singular Value Decomposition (SVD)

#### What problem does NMF solve?

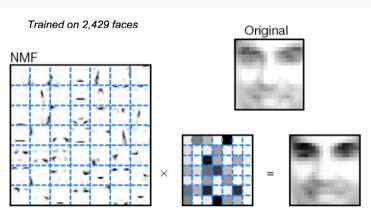
#### Soft clustering

- Clustering but where each observation can have partial membership in multiple cluster
- (.3 value for membership in "cluster\_1", .7 value for membership in "cluster\_2", ...), etc.

#### Identify latent features

- A movie can be part of many genres at once and a user can enjoy many different genres
- Nutritional values may come from many different ingredients and every recipe will have many ingredients
- Topics from documents and their corpus of text







Given a cake, we cannot directly observe its ingredients. To keep it simple we'll imagine that only two are needed right now.

[flour (F) and sugar (S)]

The specifics of the recipe are a closely guarded secret!

What's the recipe?

cake as its ingredients =  $W = [w_F, w_S]$ 



But we can directly measure its macronutrients:

(carbohydrates (c), proteins (p), fats (f))

e.g., the cake is made of 50g of carbohydrates, 10g of proteins, and 3g of fats

cake as macronutrients = [50, 10, 3]

$$\mathbf{V} = [\mathbf{v}_{c}, \mathbf{v}_{p}, \mathbf{v}_{f}]$$

#### **Nutrition Facts** Serving Size 2 Tbsp (30g) Servings Per Container 10 **Amount Per Serving** Calories 70 Calories From Fat 45 % Daily Value\* Total Fat 5q Saturated Fat 3.5g 18% Sodium 170mg 7% Total Carbohydrate 6g Sugars 5q Protein 1a Vitamin A 0% Vitamin C 0% Calcium 0% Iron 4% \*Percent Daily Values are based on a 2.000 calorie diet.

Ingredients are themselves made of macro nutrients

(for which we know the proportions)

- 1 cup flour is made of 20g of carbohydrates,
   5g of proteins, and 1g of fat
- 1 cup sugar is made of 10g of carbohydrates,
   0g of proteins, and 1g of fat

```
macronutrients from ingredients = [[ 20 , 5 , 1 ], [ 10 , 0 , 1 ]]
```

Or to generalize 
$$\mathbf{H} = [[h_{F,c}, h_{F,p}, h_{F,f}], [h_{S,c}, h_{S,p}, h_{S,f}]]$$

MEATS AND FISI	H					Mackerel, 6 oz. (Atlantic)	348	31.5	0	23.5	0
	CALORIES	PROTEIN	CARSS	FATS	FIBER	Beef patty, 1 (95% lean)	141	22	0	5	0
Beef, eye of round, 8 oz.	448	77	0	13	0	* Items are ranked by pro	tein content	in grams, fr	om highes	t to lowe	.52
Turkey, leg meat, 8 oz.	356	65.5	0	8.5	0	NOTE: USDA nutrition d ranking by protein conti	atabase serv	ings range f	rom 6-8 o	unces; th	10
Venison, top round steak, 7 oz.	310	64	0	4	0	variation of the meat an	d fish items.	take into ac	COUNTING	siight we	gnt
Beef, ribeye, 8 oz.	521	63	0	29	0	FRUITS					
mu, fan fillet, 7 oz.	308	62.5	0	4.5	0	THOUSE THE PARTY OF THE PARTY O	-	-			-
filet mignon, 8 oz. tenderloin)	494	62	0	25	0	Raspberries, 1 cup	CALORIES 64	PROTEIN 1.5	CARBS 15	FATS	*FIBE
lank steak, 8 oz.	457	62	0	20	0	Blackberries, 1 cup	62	2	14	0.5	7.5
lk, 7 oz.	292	60.5	0	4	0	Pear, 1 medium	103	0.5	27.5	0	5.5
lison, 8 oz. (ground)	405	59	0	19	0	Avocado, ½ cup cubed	120	1.5	6.5	11	5
ri-tip (sirloin), 8 oz.	478	59	0	25	0	Apple, 1 medium	95	0.5	25	0.5	4.5
Beef, liver, 7 oz.	382	58	10	10	0	with skin	100			7.0	
strich, 7 oz.	312	57	0	7.5	0	Kiwi, 2 2-inch fruit	84	1.5	20	0.5	4
outside strip)	312	47.		1.0	U	inge, 1 medium	69	1	17.5	0.5	3.5
Extra-lean ground seef, 7 oz.	526	56	0	32	0	Blueberries, 1 cup	84	1	21.5	0.5	3.5
Sison, top sirloin, 7 oz.	332	54.5	0	11	0	Banana, 1 medium	105	1.5	27	0.5	3
Bison steak, 3.5 oz.	324	54	0	6	0	Strawberries, 1 cup sliced	53	1	13	0.5	3
urkey breast, 8 oz.	304	54	0	6	0	Pineapple, 1 cup	0.0			-	-
hicken thigh, 7 oz.	418	52	0	22	0	chunks	82	1	22	0	2.5
meat only)	418	52	0	44	0	Papaya, 1 cup cubed	55	1	14	0	2.5
ef, top loin, 8 oz. (Y. strip)	313	52	0	-11	0	Peach, 1 medium	58	1.5	14.5	0.5	2
ed snapper, 7 oz.	256	52	0	2	0	Grapefruit, ½ fruit	52	1	13	0	2
icken breast, 8 oz.	248	52	0	4	0	Tomato, 1 cup chopped	38	2	8	0.5	2
wordfish, 7 oz.	310	51	0	10	0	Cantaloupe, 1 cup	54	1.5	13	0.5	1.5
eef, top sirloin,	and the same		and the last	- NAME -		Cherries, ½ cup pitted	49	1	12	+ 0	1.5
oz. (lean cut)	456	46	0	29	0	Grapes, 1 cup	62	0.5	16	0.5	1
Orange roughy, 7 oz.	210	45	0	2	0	Items are ranked by fibe	r content, in	grams, from	highest t	o lowest	7
rime rib, 8 oz. small end, lean)	576	44	0	43	0	NUTS AND SEED				_	
Beef, short loin, r-bone, 6 oz.	300	44	0	12.5	0	HOIS MIND SELL		****			
Halibut, 1/2 fillet	224	42.5	0	4.5	0	The state of the s	CALORIES	PROTEIN	CARBS	'FATS	FIBER
Deli ham, 7 oz.	290	42.5	2	12	0	Brazil nuts, 1 oz.	186	4	3.5	19	2
ork tenderloin, 7 oz.						Walnuts, 1 oz. (14 halves)	185	4.5	4	18.5	2
lean meat only)	218	42	0	4.5	0	Sunflower seeds, 1 oz.	175	5	6	16	3.5
Atlantic cod, 1 fillet	189	41	0	1.5	0	(toasted without sait)	10000	751	100	100	0.0
'una fillet, 6 oz. bluefin)	244	40	0	8	0	Almonds, 1 oz. (whole kernel)	165	6	5.5	14.5	3
ładdock, 1 fillet	168	36.5	0	1.5	0	Peanuts 1 oz.	161	7.5	4.5	14	2.5
rout, 6 oz.	252	36	0	11	0	(no salt) Pumpkin seeds.	THE REAL PROPERTY.	100000	10000	120000	-
Filapia fillet, 6 oz.	216	36	0	6	0	1 oz. dried	158	8.5	3	14	1.5
Shrimp, 6 oz.	168	35.5	0	2	0	Soybeans, 1/4 cup					
Salmon fillet, 6 oz. (Atlantic, farmed)	312	34	0	18	0	(mature seeds, dry roasted)	194	17	14	9.5	3.5
Salmon fillet, 6 oz. (Atlantic, wild)	242	34	0	n	0	Flaxseeds, 1 tbsp. whole	55	2	3	4.5	3
Sole, 6 oz.	154	32	0	2	0	items are ranked by fat or	content in a	rams from h	inhest to	owest	

Figuring out the recipe is about solving the following equation:

```
[ recipe of cake as ingredients ] *
[ macronutrients from ingredients ]
```

= [cake as macronutrients]

$$W * H = V$$

$$[w_F, w_S] * [[20,5,1], = [50,10,3]$$
  
 $[10,0,1]]$ 

So... we could try to solve for W now, but first let's think bigger.





Serving Size 2 Tbsp (30g) Servings Per Container 10 Amount Per Serving Calories 70 Calories From

Calories 70 Calories From	Fat 45
% Daily	Value*
Total Fat 5g	8%
Saturated Fat 3.5g	18%
Sodium 170mg	7%
Total Carbohydrate 6g	2%
Sugars 5g	
Protein 1g	

Nutrition Facts

Vitamin A 0% • Vitamin C 0%
Calcium 0% • Iron 4%
\*Percent Daily Values are based on a

Using MANY known values for H and V:

$$W * H = V$$

Solve for W from set of linear equations? These numbers are approximate so we're guaranteed to get error.

Minimize approximation error using Ordinary Least Squares solver!





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Sugars 5g	
Protein 1g	
Vitamin A 0% · Vitamii	n C 0%
Calcium 0% • Iron 49	%

Percent Daily Values are based on a

**Nutrition Facts** 

Let's focus on that first row for now.

$$[[w_{1,F}, w_{1,S}]] * [[20,5,1], = [[50,10,3]]$$

\_\_\_\_\_

$$20 w_{1,F} + 10 w_{1,S} = v' \approx v_{1,c} = 50$$

$$5 w_{1,F} + 0 w_{1,S} = v' \approx v_{1,p} = 10$$

$$1 w_{1,F} + 1 w_{1,S} = v' \approx v_{1,f} = 3$$

$$argmin \qquad ||\mathbf{V'} - \mathbf{V}||^2$$

$$\mathbf{W} = [[w_{1,F}, w_{1,S}]]$$

Find W that minimizes the reconstruction



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$$W * H = V$$

First Problem: What if we only knew W and V instead of H and V? Can we get

#### Generalization: Unbaking cakes

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First Problem: What if we knew W instead of H? Can we get H?

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$$2 h_{F,p} + 1 h_{S,p} = v' \approx v_{1,p} = 10$$

$$2 h_{F,f} + 1 h_{S,f} = v' \approx v_{1,f} = 3$$

$$1 h_{F,c} + 1 h_{S,c} = v' \approx v_{2,c} = 30$$

$$(... and so on)$$

$$argmin || \mathbf{V'} - \mathbf{V} ||^2$$

$$= [[ h_{F,c}, h_{F,p}, h_{F,f}], [ h_{S,c}, h_{S,p}, h_{S,f}]]$$

Find H that minimizes the reconstruction error

#### Generalization: Unbaking cakes

W \* H = V

The Real NMF Problem: What if we don't know either W or H?

What would solving **W** and **H** give us when we have zero ingredient information!

With enough cake nutrition info in **V**, we could find **W** and **H** that multiply to reconstruct **V** with some error. That means we could simultaneously figure out what the underlying ingredients might be *and* how nutritious each ingredient is. (We'd have to inspect the results to see that they make sense and guess at what those ingredients are!) If only there were some way to approach good **W**s and **H**s through some iterative process that minimizes the error...

That's what NMF is for!

# What is the Non-Negative Matrix Factorization Algorithm?

galvanize

#### Let's Look at the Matrices Again

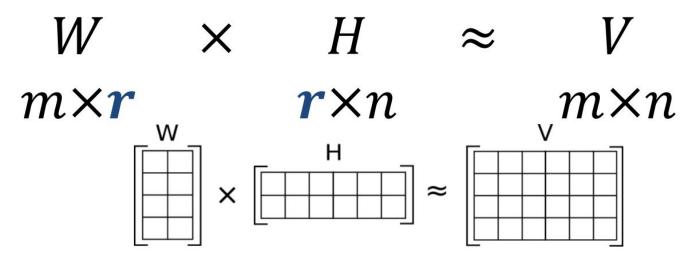
$$W_{m\times r} * H_{r\times n} = V_{m\times n}$$

We put ourselves under the restriction that all of W and H are non-negative. There's no "negative flour" and no "negative movies" in a film genre:

$$w_{i,j} \ge 0$$
 and  $h_{k,l} \ge 0$ 

**r** is an integer we can choose as our guess at how many latent topics (e.g. unique cake ingredients) we think there might be.

#### Let's Look at the Matrices Again



- r is set by you  $(r < \min(m, n))$
- Cannot be solved analytically, so approximated numerically
- When r > min(m, n), we can perfectly recreate V as  $W \cdot H$
- otherwise, some sort of data compression is happening



### Let's Look at the Matrices Again

We call this type of optimization problem biconvex as it's convex in either **W** or **H** but not both. That means if we know one of them and **V**, we could solve for the other by minimizing the reconstruction error. There's a straightforward way we can brute force an approximate solution if this is the case.

While there is no closed form solution for **W** and **H**, if we hold one of these matrices constant, there is a closed form optimum for the other.

This leads us to the **Alternating Least Squares** algorithm.

## Here's the Alternating Least Squares Algorithm That We'll Use in Today's Sprint

We will take advantage of the biconvexivity by alternating which matrix, **W** or **H**, that we treat as stationary, solving for the other's optimal values, and then *clipping* all the negative values in that solution to 0.

#### Pseudo-code:

- 1. Initialize W to small, positive, random values
- 2. Repeat
  - 2.1. Find the least squares solution to  $X = W \cdot H \text{ w.r.t. H.}$
  - 2.2. Clip negative values in H to 0: H < 0 = 0.
  - 2.3. Find the least squares solution to  $X = W \cdot H \text{ w.r.t. } W$ .
  - 2.4. Clip negative values in H to 0: W < 0 = 0
- 3. Stop when convergence (i.e., some threshold is met) such as maximum iterations or small enough decrease in RMSE.

## Here's the Gradient Descent Version! (no need to clip!)

### Minimize $||V - WH||^2$ with respect to W and H subject to $W, H \ge 0$

#### <u>Steps</u>

- (1) Start with some random W and H (random, small positive values)
- (2) Repeatedly adjust W and H to make RMSE smaller

$$H_{a\mu} \leftarrow H_{a\mu} \frac{(W^T V)_{a\mu}}{(W^T W H)_{a\mu}} \qquad W_{ia} \leftarrow W_{ia} \frac{(V H^T)_{ia}}{(W H H^T)_{ia}}$$

 $(H_{a\mu} \text{ and } W_{ia} \text{ are single entries in } W \text{ and } H)$ 

- This is gradient descent! It's simple but can be slow. The convergence is sensitive to choice of step size.
- (3) Stop when some threshold is met
  - Decrease in RMSE, # of iterations, etc.

# Another Use Case: Topic Modeling for Natural Language Processing

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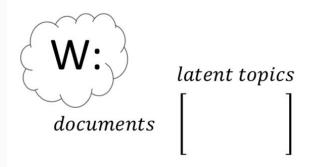
## Topic Modeling with NMF

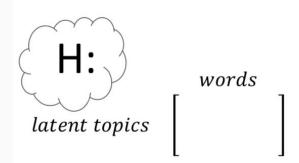


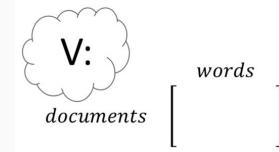
$$V \approx W \cdot H$$

```
cake ingredients cake
as ⋅ as ≈ as
ingredients macro nutrients macro nutrients
```

```
document topics document
as · as ≈ as
topics words words
```







- In looking at the dimensions of W, we notice that the number of rows remain the same, as we would expect. Thus, each row of W must represent some information about the corresponding row in V.
- Think of the column W as <u>latent topics</u> where the higher the word's cell value, the higher the word's rank for that latent feature.
- The same can be said about H: the number of columns between V and H are the same. Thus, each column of H must represent some information about the corresponding column in V.

#### Choosing k?

- Choosing k is more of an art than a science. We can look at how "good" of an approximation WH is for V and try to find the smallest k that makes it suitably small.
- At the end of the day, though, k, is likely going to be chosen based on intuition that you derive from inspecting the topics and possibly from some domain knowledge.

k x m

## Example *H* Matrix

"president"	"coach"	 "team"	_
0.3	5.1	 4.2	Topic 1
10.3	1.07	 0.08	Topic 2
	:	 :	
		 	1
2.03	0.3	 0.001	Topic k

Topic 1? Sports?
Topic 2? Politics?



## Key Takeaways

NMF

- Creates two smaller matrices with lower rank than the original matrix that tell us about underlying similarities in the rows of data.
- This creates one matrix that describes "latent topics" as composed of the original feature values and a new matrix that describes the original data as made of those topics.

galvanıze

## Key Takeaways

Things that will help with understanding PCA tomorrow

- Other algorithms can be used to reduce dimensionality through matrix factoring similarly to NMF. They don't produce easily interpretable "topics" the same way and that's fine! Different tools for different needs.
- PCA and SVD are two common tools that rely on feature covariance to try to find how similarly features vary together and then creates a new way to describe those features by this similarity.
- Unlike NMF, there are unique solutions for these matrices.



#### Non-negative matrix factorization

