Inspiring healthy habits: data science at WW

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Outline

- Intro to WW: purpose, program, type and scale and data
- Behavioral Nudges
- WW Data Products
- Primrose: how we develop and deploy ML models
- Q&A



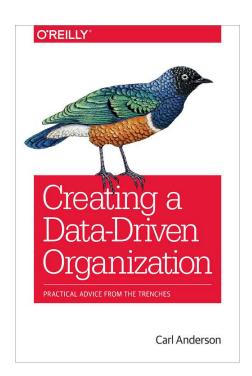


About Me

Data Strategy

Data Science

Business Intelligence Engineering

















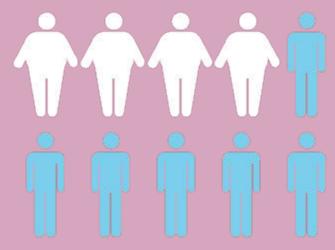








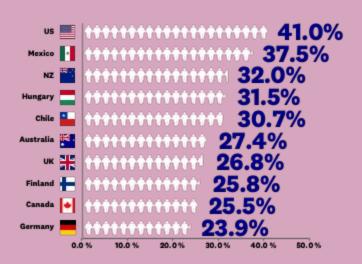
40% of adults on the planet are already overweight or obese and more are joining their ranks every day



While the world's bulging waistlines are driven by economic success—wealthy populations eat more—obesity's estimated cost of \$2 trillion a year worldwide is now almost as much of a financial burden as smoking.

Source: TIME Health. New England Journal of, Medicine Institute of Health Metrics and Evaluation, OECD (2017)

Top 10 countries ranked by percentage of adult population that is obese in 2015 or nearest year





HEALTH PARADOX #1

We spend more time and money than ever before on wellness, but we've never been more unhealthy.



HEALTH PARADOX #2

Despite all the advances in science and food production, eating healthy has never felt more complicated.



Confusing headlines have left many in a fog and unsure what to do

5 Reasons You Need to Count Calories

5 Reasons To Never **Count Another Calorie**

Why Sugar isn't the Bad Guy

10 Disturbing Reasons Why Sugar is Bad for You

JUNK SCIENCE: Gluten is Not Bad For You

Why Gluten is Evil Grains and Autoimmune Disease

RED MEAT: It Does a Body Good!

THE SECRET IS OUT:

THE REASON RED MEAT IS **BAD FOR OUR HEALTH**

> New study finds organic foods are healthier than conventionally grown foods

THE ORGANIC FOOD LIE

People want inspiration, not just information.

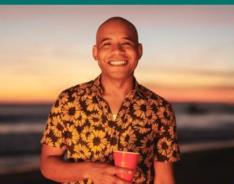


People want healthy habits that fit their lives.





Today, healthy is the new skinny.



It's not about lifestyle, it's about livability.





People crave purpose.













Social

Body







Mental







TENET #1

We help you build powerful habits, rooted in science.



TENET #3

We enable you to find and form inspired communities.



TENET #2

We know you and meet you where you are.





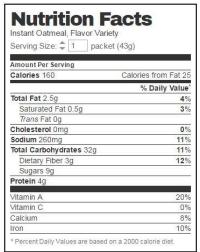


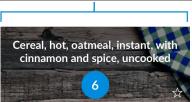
SmartPoints is about health, not just calories

All calories are NOT created equal.



Nutritional science to make healthy eating simpler





SmartPoints nudges you towards a healthy eating pattern with more fruits, vegetables and lean protein, and less sugar and saturated fat.

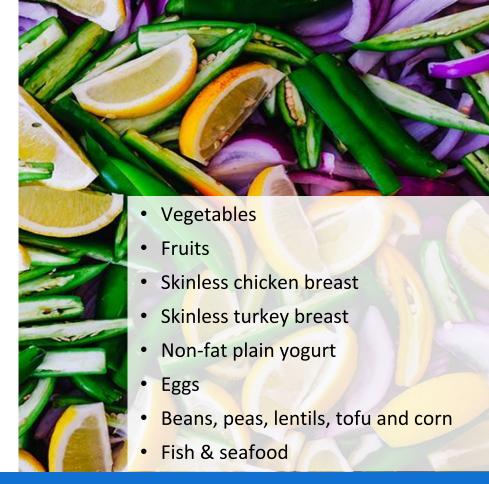
- Calories establish the baseline.
- Sugar and Saturated Fat increase the SmartPoints value.
- Protein lowers the SmartPoints value.
- Foods that form the foundation of a healthy eating pattern have SmartPoints value of zero.



ZeroPoint™ Foods

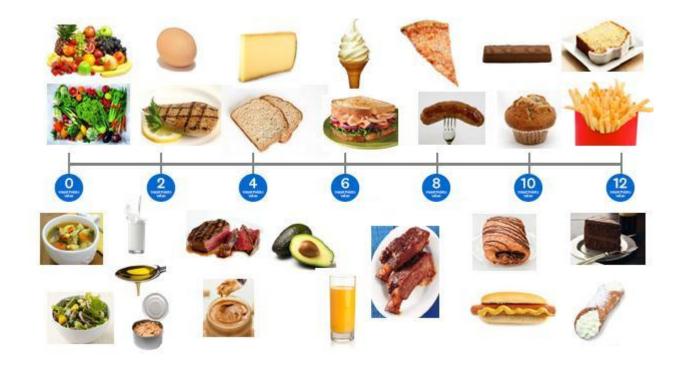
ZeroPoint foods form the foundation of a healthy eating pattern and have a low risk of overeating.

They don't have to be weighed, measured, or tracked.



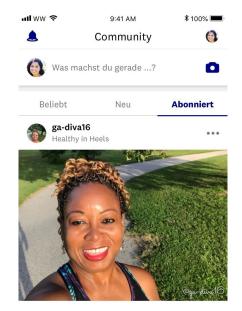


Everything is on the menu





App



TGIF! Ich bin gerade dabei ...











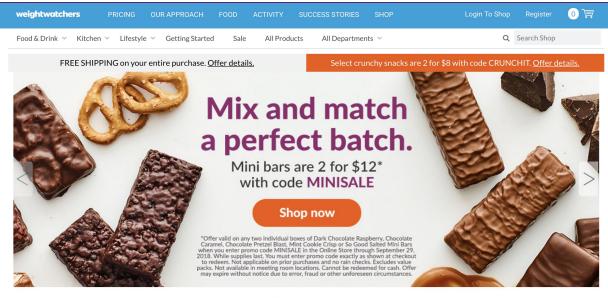
WW Studio

30,000 meetings per week globally





eCommerce



NEW ARRIVALS



Weight Watchers Magazine September/October Issue \$4.95



Buttermilk Protein Pancake



Best of WW Mini Cookbook Bundle \$11.95



Snickerdoodle Baked Protein Mini Bar \$5.95



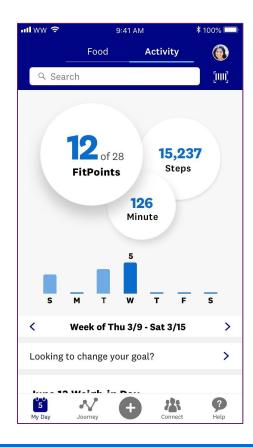
Triple Chocolate Baked But Protein Mini Bar \$5.95

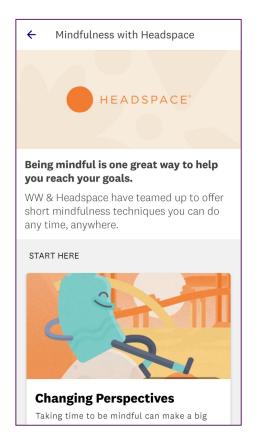


Butter Popcorn - Pack of 6 \$7.95



Activity & Mindset







Voice & Al

Google Assistant

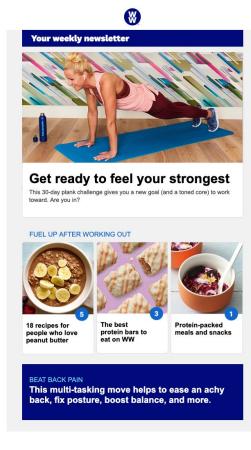
Alexa







Newsletter





kurbo

Proven digital health solution for teens and children





Kurbo by € How it works Ou

The simple, proven program to get healthier & lose weight

Try Kurbo for 7 days, free!

My employer or health insurance provider pays for Kurbo >



How Kurbo helps you lose weight & build healthy habits



Follow the traffic light system

Green, yellow or red lights make it easy to pick good foods. It's simple and clear that's why kids and teens like it.



Track on your phone

Our app keeps you on track and makes weight loss fun with videos, challenges, and cool backs to try.



Work with

Because kids and teens who work with a Kurbo coach are 10x more likely to reach their weight loss and get-healthy goals!

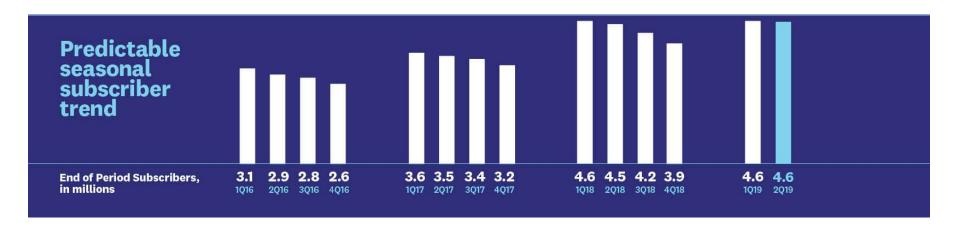


JARED. lost 18 lbs

"I feel more confident, healthier, and more comfortable in my skin."

Read all the success stories >

Dynamics and Scale



In Q2,

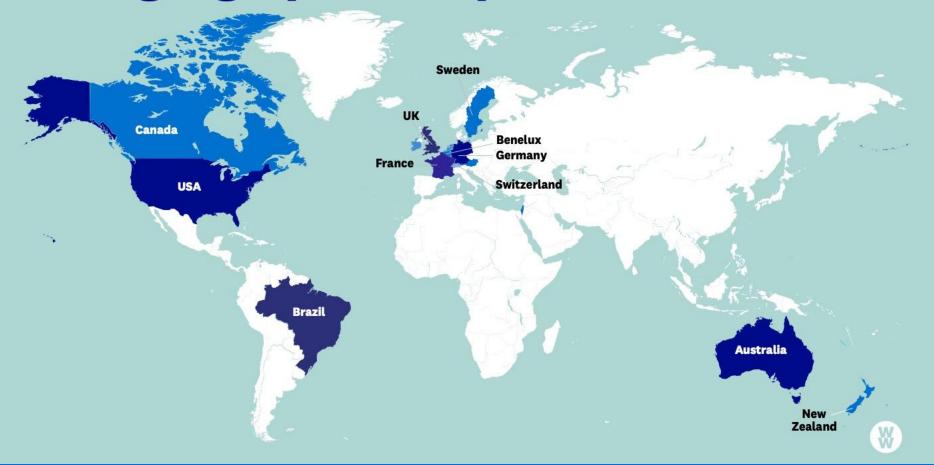
Social network:

- 2 million posts
- 14 million comments
- 70 million likes

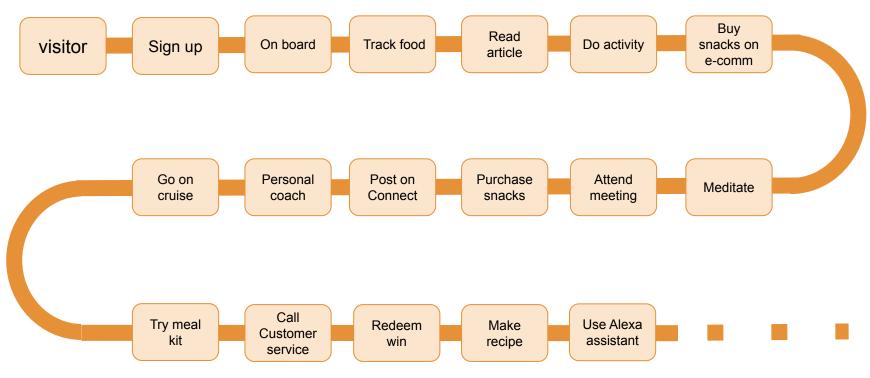
1 million members tracked a physical activity



Our geographic footprint



Member Journey (Illustrative)



Almost none of this is personalized!





Big data:

- Food
- Activity
- Exercises
- Challenges
- Social network
- Workshops
- Personal Coaches
- CRM
- Fulfillment
- Meal kits
- Supermarket foods
- E-commerce
- Cruises

...for 56 years



Scale of Data

- Nackers et al (2013) showed that fast (≥0.68 kg/week) weight loss in the first month predicts higher weight loss success at 6 months than slow (<0.23 kg/week) or moderate initial weight loss
- Sample size: 298
- We checked our weigh in data to compare these results to what we observe in our member base

Nackers, Ross & Perry (2013). The Association Between Rate of Initial Weight Loss and Long-Term Success in Obesity Treatment: Does Slow and Steady Win the Race? *Int J Behav Med.* 17(3):161-167.



Scale of Data

- Members considered:
 - 1) started and ended their membership between Apr 2017 and Apr 2019
 - 2) were members for at least 6 months
 - 3) weighed in in their first week, fourth week and sixth month
 - 4) were obese at the beginning of their membership (BMI > 30)
- For all analyses (mostly) unfiltered self report data was used.

Sample size: 211,000 members!



7kg median weight loss after 6 months

- 211k members
- 54% digital (sampling bias)
- Mostly female
- Median birth year 1971
- Median start BMI: 35
- Median BMI @ 6 months: 32.5

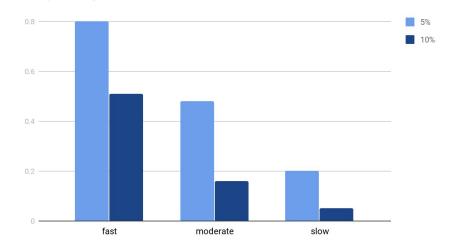




Significant effect of initial weight loss rate on weight loss success

- Weight loss defined as 5% or 10% of initial start weight lost
- Initial weight loss speed:
 - Fast (≥0.68 kg/week): 116,107
 - Moderate (<0.68 & >0.23 kg/week):
 61,204
 - Slow (<0.23 kg/week): 34,107

Proportion of members who lost 5% or 10% initial body weight at 6 mo



*all differences statistically significant



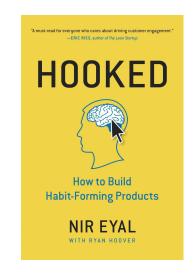
Nudges & behavioral change



Healthy Habits

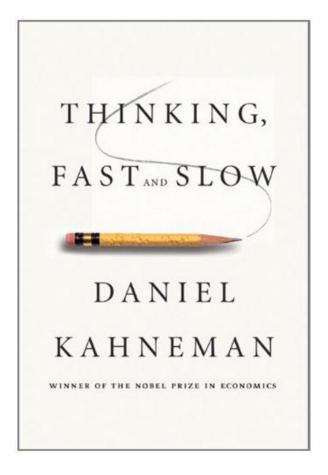
Habit:

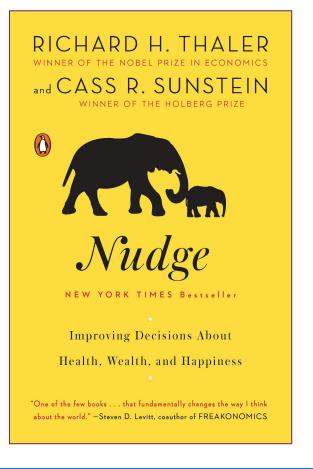
"Automatic behaviors triggered by situational cues"



"Habit-forming companies link their service to the users' daily routines"











"Any addition to or modification of the environment that influenced consumers in a predictable way, without changing economic incentive"

Altering environment by changing presentation of options — called **choice architecture**





"Any aspect of the choice architecture that alters people's behavior in a predictable way (1) without forbidding any options or (2) significantly changing their economic incentives. Putting fruit at eye level counts as a nudge; banning junk food does not."



Nudging & Choice Architecture

i**N**centives

Understand mappings

Defaults

Give feedback

Expect error

Structure complex choices

This is Thaler & Sunstein's framework. Instead, I will use Blumenthal-Barby & Burroughs



Nudging & Choice Architecture

Category	Explanation	Examples
Priming	Subconscious; physical, verbal, sensational	Place unhealthy options out of sight or farther away in cafe
Salience	Informational; attention grabbing; emotional	Calorie label; graphic image on cigarette cartons; recommenders
Default	Pre-set default choice; good option for do-nothing behavior	Automatic opt-in, have to explicitly change or opt-out: benefits, organ donation
Incentive / Gamify	Reward or punish for behavior; recognition	Badge; coupon; \$\$?
Commitment / Ego Get someone to make a commitment; leverage ego, pride		Sign up for 5k; invest (pay for membership); share with friends
Norms / Messenger	Use other to establish a norm and for consumer to compare themselves	80% of (other) people are organ donors; most people wear seatbelts

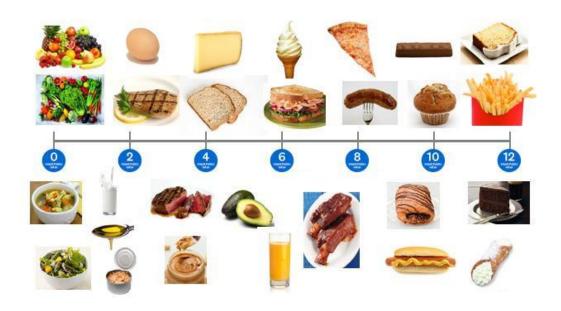
Blumenthal-Barby & Burroughs. (2012). Seeking better health care outcomes. The ethics of using the nudge. Am. J. Bioethics 12(2):1-10.







Everything is on the menu



Members are empowered with lots of choices.

We are not dictating diet, exercise regime etc. Hence, these are nudges



Priming

Visibility, accessibility, available



Further prime by reducing friction for key actions such as tracking



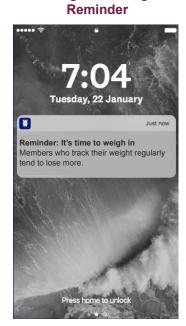




Priming

Visibility, accessibility, available

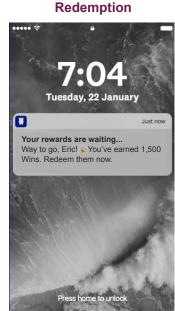
We plan to leverage notification nudges, similar to these, to help keep people on track



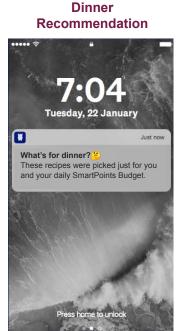
Weight Tracking



Wellness Wins



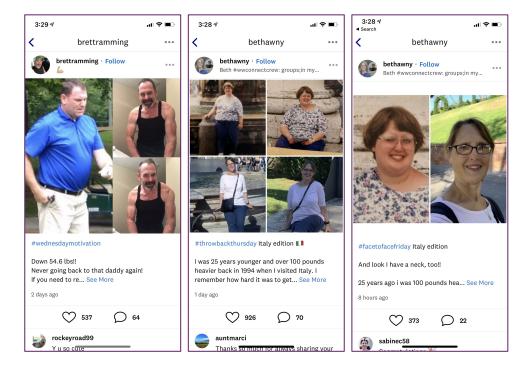
Wellness Wins





Priming

Visibility, accessibility, available



Connect social network: very highly supportive, lots and information from staff and fellow members. Priming and saliency.



meaningful, relevant info



Greek yogurt & fruit and peanut parfait



Scrambled eggs, Canadian bacon, avocado, tomato and English Muffin



Pancakes with chocolate chips and maple syrup

- Points on very large number of foods
- Clear "mappings" make it easier to make good choices:
 - instead of calorie counting, 300 cal (or is it kJ, kcal) \rightarrow 5 points



of an adult's Reference Intake.
Typical values (as sold) per 100q: Energy 1322kJ/316kcal



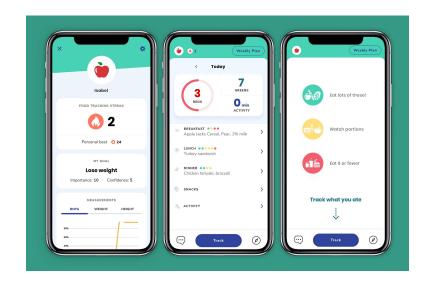
Saliency meaningful, relevant info



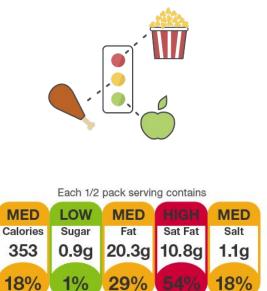
- Clear budget
- Clear progress



meaningful, relevant info



Kurbo traffic light system



of your guideline daily amount Source: Food Standards Agency

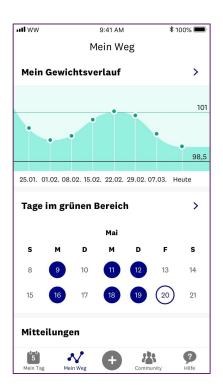
UK nutrition labels



meaningful, relevant info

Activities are also pointed: FitPoints







meaningful, relevant info

















Tracking and wearables

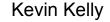




Quantified Self

self knowledge through numbers

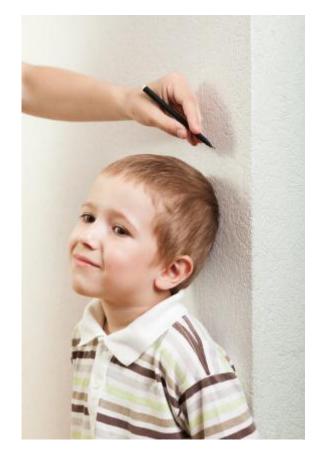






Gary Wolf









Girolamo Cardano 1501-1576

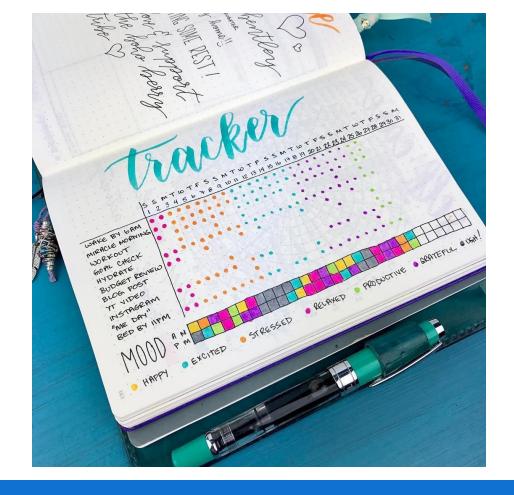




Santorio, Santorio 1561-1636







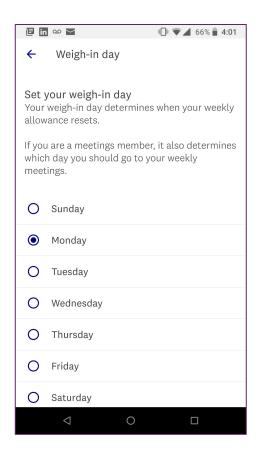


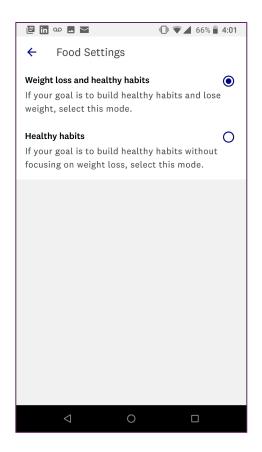




Defaults

- Defaults should be good, fair, equitable...
- Easily changed



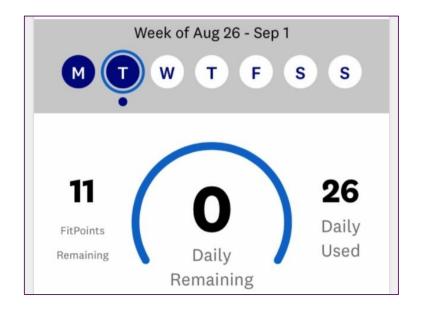








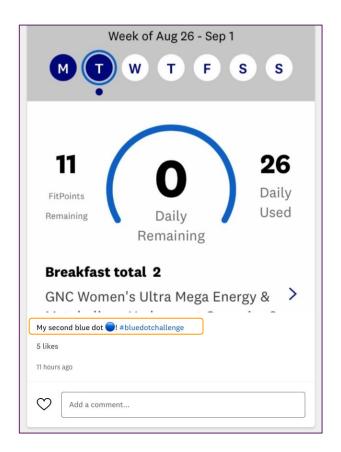


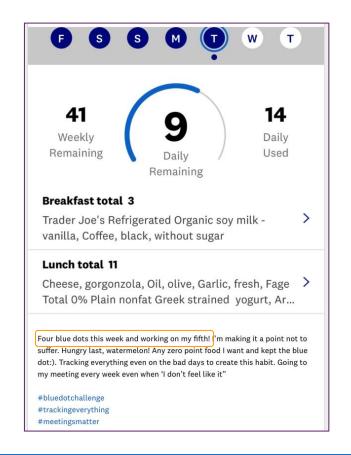




Blue dot: daily, weekly, monthly









WellnessWinsTM

A first-of-its-kind program that rewards members for building healthy habits.

You earn "Wins" for:

- Tracking meals (breakfast, lunch, dinner)
- Tracking activity
- Tracking weight
- Attending workshops



WellnessWins celebrates outcomes

Milestones are rewarded for:

- Weight loss: 5, 10, 25, 50, 75, 100, 125, 150, 175 & 200 lbs
- Goal weight

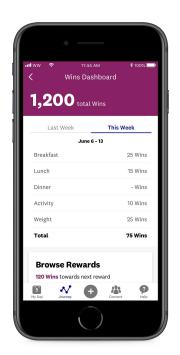
"I've got my keyring with all my little bangles hanging off of it. I love that thing. It might seem stupid but it was just fun to get those rewards along the way, a physical manifestation of your success"







































WellnessWins is motivating

We are holding members accountable while making it fun to earn

The silver lining of this past super difficult week. is that I'm down 2.2 lbs. Not a big loss, but I'll take it! I think #wellnesswins is just what I needed to lift my spirits & motivate me to track, track, & track some more!!

I've tracked EVERYDAY for the past 30 days. That hasn't happened in years!!! I'm very excited

take it! I think #wellnesswins is just what I needed to lift my spirits & motivate me to track, track, & track some more!! 69

I am SO EXCITED about this! I need a change of pace and the #WellnessWins program is coming at the best time &



I've tracked EVERYDAY for the past 30 days. That hasn't happened in years!!! I'm very excited for the #wellnesswins incentives to keep me motivated. Hoping to be back within my lifetime range by the end of th... See More

1 minute ago

My app is updated! It's Workshop day! So excited for WellnessWins! Happy WW made changes in October not December! I needed something to re-ignite my WW journey besides my Why...the timing is perfect!

#app #wellnesswins #ranchosandiego

I updated my app and I am SO excited! I love achievements and this is definitely an amazing motivator to track and weigh in! Love love! #wellnesswins



...











lizbuck7



Totally! Me too!



welshbirdinidaho

Hahahaha I was thinking the same thing



dero316

Me too! My kind of motivation!!!



sdrier1 · Follow



I'm really excited for #wellnesswins! I feel it will give me that little motivational push that I really need right now!

Haven't tracked this consistently in months.



marouzan · Following Martine LT WW Coach









Remaining



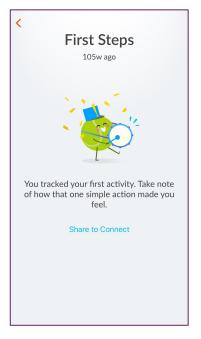
1 84%

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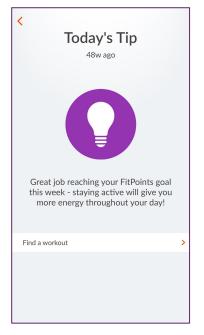


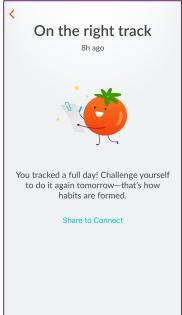


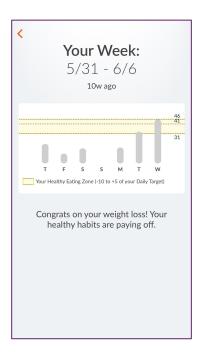


Recognition helps motivate







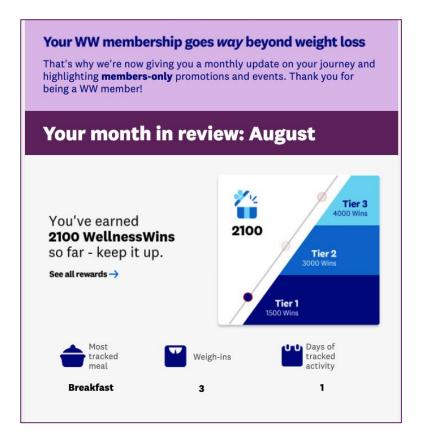


Recognition helps motivate





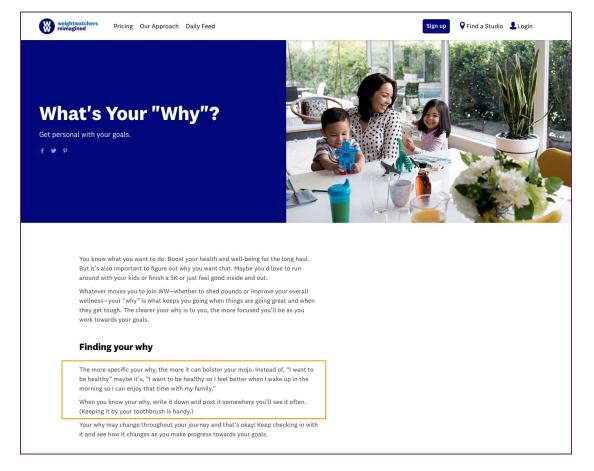






Motivation

- Member is doing the work.
- Important for them to remind themselves why they are doing this





Willpower

"Weight Watchers, for example, coaches dieters to use an array of self-deployed situational and cognitive strategies and, in addition, sponsors in-person meetings, communicates social norms, and provides a phone app to track eating and exercise"

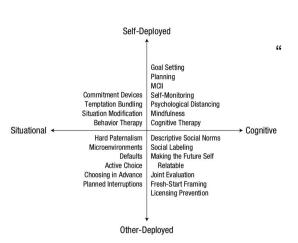


Fig. 2. Illustrative examples of approaches aimed at reducing self-control failures. Approaches are classified as situational versus cognitive and self-deployed versus other-deployed. MCII = mental contrasting/implementation intentions.

Strategy	Example	
Self-deployed situational strategies		
Commitment devices	Decision maker commits to eat a serving of fruit and vegetables at dinner every night, asks spouse to serve as a referee, and puts money on the line that will be forfeited to spouse in case he or she fails to meet this commitment.	
Temptation bundling	Decision maker listens to a favorite music album only when cooking dinner from scratch (rather than eating fast food).	
Situation modification	Decision maker stocks up on bags of Halloween candy for trick-or-treaters—but only cand that she does not like.	
Behavior therapy	Decision maker works with a therapist, learning to identify triggers that result in junk food binges (e.g., deadlines at work) and also alternatives (e.g., taking a walk) that can meet the same needs (e.g., stress relief).	
Self-deployed cognitive strategies		
Goal setting	Decision maker decides: "I will eat a fruit or vegetable with every meal!"	
Planning	Decision maker plans: "If it is 8 a.m., then I will look in the refrigerator for some fruit to have with my breakfast."	
Mental contrasting with implementation intentions	Decision maker thinks: "The best outcome of eating healthy is that I will have more energ. The obstacle that stands in the way is that I don't have time to go shopping. My plan is: If it is Saturday morning, then I will take a nice walk to the grocery store to buy fresh fruit that I'll then eat."	
Psychological distancing	Decision maker reframes situation using third-person perspective: "Angela is hungry and has a choice between a bag of potato chips and an apple. Which should she choose?"	
Mindfulness	Decision maker introspects: "I notice that I'm craving potato chips. I accept that I have thi urge. I may or may not act on it."	
Cognitive therapy	Decision maker works with a therapist, learning to ask, "What thoughts lead me to snack on potato chips in the afternoon? Do I think, 'I can't resist junk food. I have no self-control at all!' And is that a reasonable thought? Or am I exaggerating?"	

Duckworth, Milkman, & Laibson. (2018). Beyond willpower: strategies for reducing failures of self-control. Psychological Science in the Public Interest. 19(3) 102–129

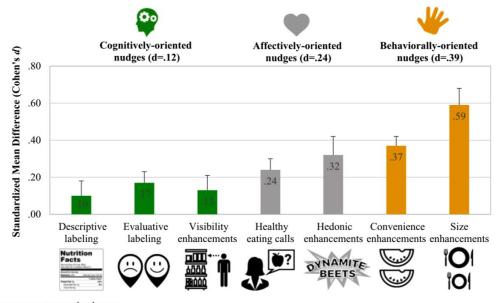
110



Duchworth at al

Effect Sizes

Figure 3. (Color online) Effect Sizes by Nudge Type



Meta-analysis of 90 articles + 96 field experiments (299 effect sizes), average effect of healthy eating nudges of Cohen's d=0.23.

= 124 kcal change in a daily intake Or -7.2%



8 tablespoons sugar / day

Note. Error bar represents standard error.

Cadario & Chandon. (2019). Which healthy nudges work best? A meta-analysis of field experiments. *Marketing Science*. DOI: 10.1287/mksc.2018.1128



Summary

Highly primed experience

easy	SmartPoints, FitPoints
available	In your pocket, AMZN, neighborhood
supportive	community

Highly saliency

progress	
food, fitness	
tips	

Incentives / Recognition at multiple temporal scales

Initial	First track, first barcode scan
Daily	Blue dot
Weekly	Weight check in
Continuous	streaks
Monthly	review
Event	Wins, milestone
Annual	Annual review???

Multiple types of recognition

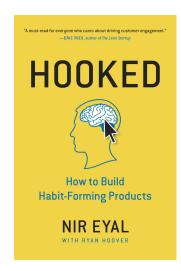
Non tangible	Badges, kudos
Peers	Connect
Goods in kind	wins

			Initial	Daily	Weekly	Monthly	Milestone	Year
	Food	Saliency		MyDay Blue dot	MyDay Blue dot	MyDay Blue dot Newsletter Month in review	badges/tips?	
		Reward & Recognition (R&R)	badges	#bluedotchallenge Badges Streaks	#bluedotchallenge Badges recommenders	#bluedotchallenge Badges Month in review	Wellness Wins badges	
		Defaults			SP budget?			
	Fitness	Saliency		MyDay	Myday	Newsletter Month in review		
		R&R	badges	badges	badges	Month in review		
	Weight	Saliency			Coaches / Meetings	Month in review		
		R&R	badges	badges	Badges Coaches / Meetings	Month in review	Wellness Wins badges	
		Defaults			Check in day			



The Hook





Data products at WW



Data products at WW



Churn model Return model LTV models Single Member View



Recipe recommender
Similar recipes
Auto-tags
Clustering member foods
Composite foods



Personalized feed Groups search Who to follow



APIs *Primrose*



A SURVEY OF FOOD RECOMMENDERS

A PREPRINT

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Weight Watchers International New York, USA carl.anderson@weightwatchers.com

September 18, 2018

ABSTRACT

Everyone eats. However, people don't always know what to eat. They need a little help and inspiration. Consequently, a number of apps, services, and programs have developed recommenders around food. These cover food, meal, recipe, and restaurant recommendations, which are the most common use cases, but also other areas such as substitute ingredients, menus, and diets. The latter is especially important in the area of health and wellness where users have more specific dietary needs and goals.

In this survey, we review the food recommender literature. We cover the types of systems in terms of their goals and what they are recommending, the datasets and signals that they use to train models, the technical approaches and model types used, as well as some of the system constraints.

 $\textbf{\textit{Keywords:}} \ \ Personalization \cdot Food \ recommendation \cdot Recommendation \ systems \cdot Collaborative \ filtering \cdot Content-based \ recommenders \cdot Expert \ systems$

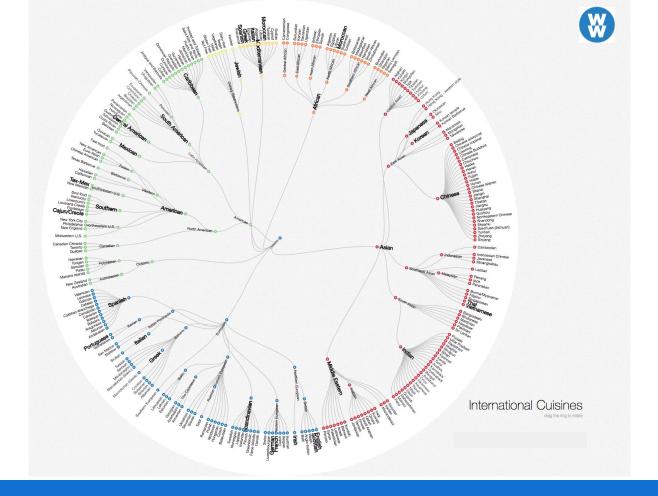
See also Trattner, C., and Elsweiler, D. (2017.) Food Recommender Systems: Important Contributions, Challenges and Future Research Directions. https://arxiv.org/abs/1711.02760



Table 1: High-level summary table that highlights the breadth of food recommender space, covering what is being recommended to whom, how, and why. * represents more speculative examples.

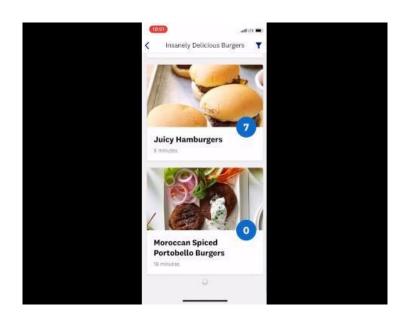
Dimension	Examples		
Who are the users?	Hungry people: you might like to order this meal		
	Cooking enthusiasts: you might like to make this recipe		
	Health-conscious : you'll love this healthy, nutritious lunch		
	Dieters : this is a low-calorie but filling and healthy meal		
	Patients: doctors suggest that you follow this diet		
What is being recommended?	Ingredient : you can substitute butter with sour cream for reduced fat and calories		
	Food : we think you'll like these summer rolls		
	Meal: we think you'll like this chicken breast plate with rice and broccoli		
	Recipe : try this pecan pie recipe		
	Recipe collection : here is a set of salad recipes you'll love		
	Restaurant: you have to try Danny's Pizza		
	Cuisine*: as you like Thai, you might like Indonesian food too		
	Diet / menu / meal plan: this is a low-sodium diet that ought to work for you		
When is it being recommended?	Realtime: where should I eat now; what's near me?		
	Batch: here is your weekly email of recipes, just for you		
Why is it being recommended?	Taste: here is something you might like to eat / make / order		
•	Health & wellness : to help people become or remain healthy, to help people lose weight and to help patients recover		

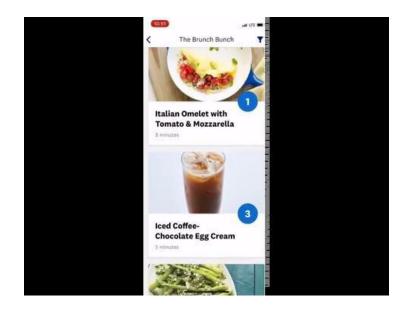






Food is at the core of our product

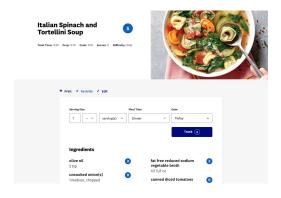






Recipe Recommendations

Similar Recipes





Dinner Recommendations





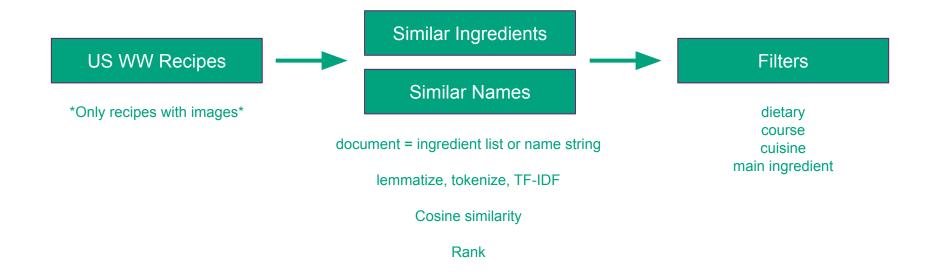
Because you tracked Grilled Salmon with Mustard-Herb Crust



```
# note: push tokenization and and handling of ngrams down to tokenize in concrete classes
self.tfidf = TfidfVectorizer(tokenizer=self.tokenize)
self.term_document_matrix = self.tfidf.fit_transform(self.docs)
def cosine_similarity_matrix(self):
    return cosine_similarity(self.term_document_matrix)
```

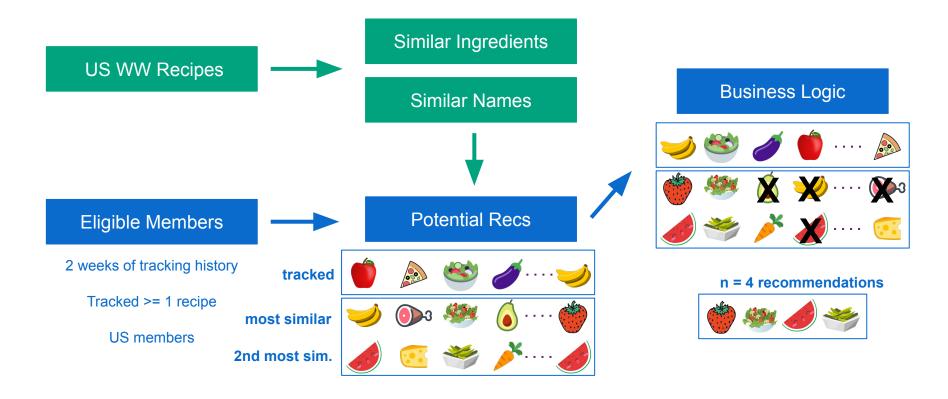


Similar Recipes Flow





Dinner Recommendations Flow





Food Embeddings



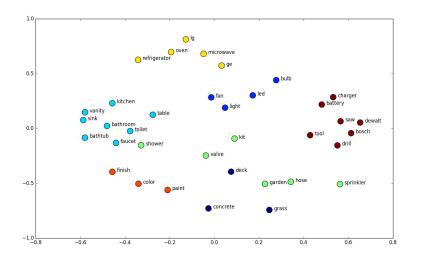




- Motivation: want to learn a space of foods where similar foods are located near each other
- Applications
 - Recommend low point substitute foods
 - o Input into recipe recommender
 - Classify new foods and users
- How to do this? Word embeddings!



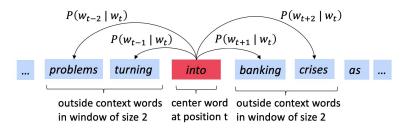
Word Embedding Overview

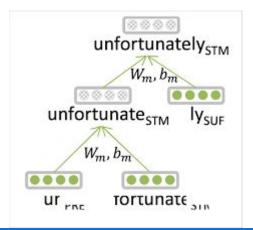


- Dense real-valued vectors representing word meaning
- **Idea:** words with similar meanings are grouped together in the embedding space
- Many forms of meaning are conflated since there is only one representation per word



FastText Behind the Scenes

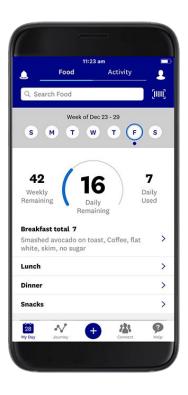




- Learns embeddings using either Skip-gram or CBOW algorithms
- But learns representations for sub-word units rather than entire words
- Representations for whole words are composed from subword representations



Preliminary Attempts



• Attempt 1 (using food log data) [1]:

- Split food names into tokens
- Each food name = 1 document
- Average token embeddings for food name
- Append calorie-normalized nutritional info
- Did not work well, but might work with better preprocessing

Attempt 2 (using recipe data) [2]:

- Context = recipe ingredients
- Each recipe = 1 document
- Did not work well, recipe data too small



Final Attempt



- Context = ordered food entries, grouped by user id and time of day (meal type) over one week
- Preprocessed data same way as in [2]
- Each "word" in a document is a whole food name
- Best result from using subword unit modeling
- Other ideas: filtering for power users

(UUID=1234, breakfast, week1) = [Monday breakfast, Tuesday breakfast, Wednesday breakfast,...]

= [coffee, toast, jam, apple, coffee, orange_juice, tea, cereal, 2%_milk, banana,...]

Will learn associations among items:

within meal: cereal ↔ 2% milk, cereal ↔ whole milk

among meals: apple ↔ banana, coffee ↔ tea

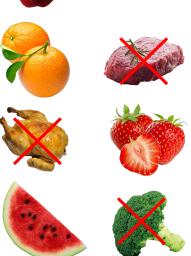


Post-processing for Substitute Extraction

Query:



Results:



- One of the main goals of the project was to extract substitute food items
- Food data contains category information
- Simply eliminate results from NN list that are not in the same category



Personalizing Social Network



Connect











Seeking positivity



Getting help



Sharing goals



Encouraging others



Making friends



Building a brand

Seeking positivity

I want to feel good and see inspirational and useful posts.



Getting help

I post when I have questions or need encouragement.



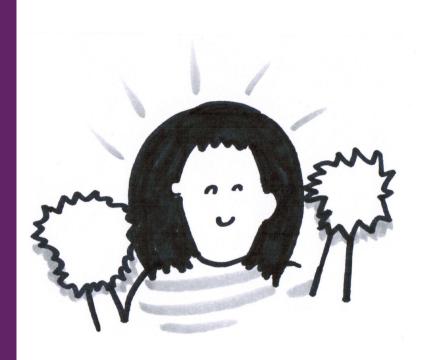
Sharing goals

I post to show what I did or am going to do.



Encouraging others

I give back the support I received to those who need it.



Making friends

I build and invest in meaningful relationships.



Building a brand

I create content to grow a large following.



"Hidden" agendas may change throughout the day or over the course of a member's journey



Personalized Feed



Your personalized feed of recommended posts

Video
Video
Content-based
Before / After



Collaborative filter



Contentbased



Videos



Before / After



Popular

Personalized Feed



The Multi-Armed Bandit Problem

- We have d arms. For example, arms are ads that we display to users each time they connect to a web page.
- · Each time a user connects to this web page, that makes a round.
- At each round n, we choose one ad to display to the user.
- At each round n, ad i gives reward $r_i(n) \in \{0,1\}$: $r_i(n) = 1$ if the user clicked on the ad i. 0 if the user clicked
- Our goal is to maximize the total reward we get over many rounds.

Thompson Sampling Algorithm

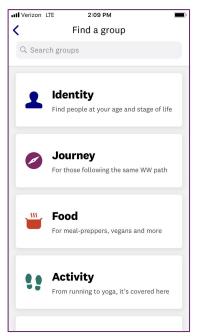
- **Step 1**. At each round n, we consider two numbers for each ad i:
 - $N_i^1(n)$ the number of times the ad i got reward 1 up to round n,
 - $N_i^0(n)$ the number of times the ad i got reward 0 up to round n.
- **Step 2**. For each ad i, we take a random draw from the distribution below:

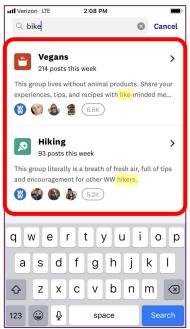
$$\theta_i(n) = \beta(N_i^1(n) + 1, N_i^0(n) + 1)$$

Step 3. We select the ad that has the highest $\theta_i(n)$.

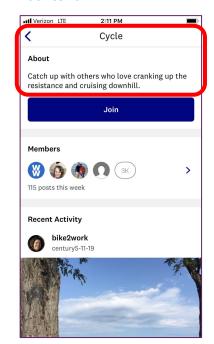
Group Search

Example: I love biking. Is there a group for this?





Issue: search only uses title and description, not content



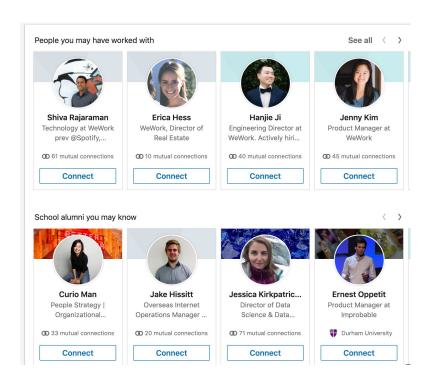
Solution: we've provided top 100 terms + top 100 hashtags per group

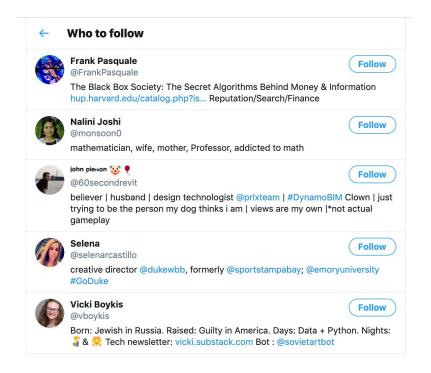
Cycle	Camping	Brides
rider	campground	bride
cyclist	tent	bridal
cycling	camping	alteration
ally	camper	bridesmaid
century	trailer	venue
biking	teardrop	seamstress
output	campfire	engagement
cadence	camped	ceremony

...

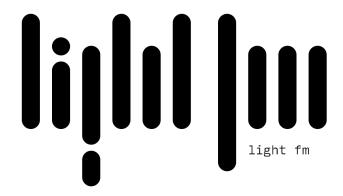






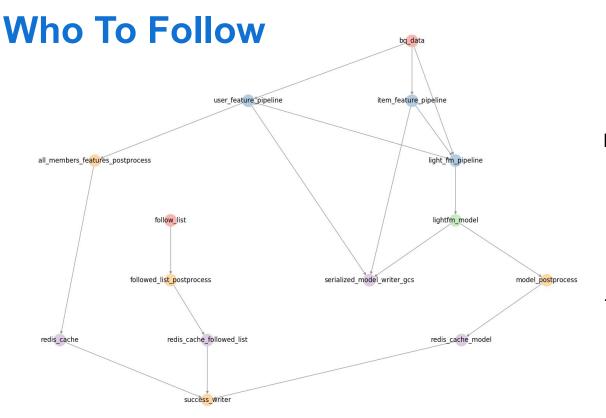






arXiv.org > cs > arXiv:1507.08439 Computer Science > Information Retrieval Metadata Embeddings for User and Item Cold-start Recommendations Maciej Kula (this http URL) (Submitted on 30 Jul 2015) I present a hybrid matrix factorisation model representing users and items as linear combinations of their content features' latent factors. The model outperforms both collaborative and content-based models in cold-start or sparse interaction data scenarios (using both user and item metadata), and performs at least as well as a pure collaborative matrix factorisation model where interaction data is abundant. Additionally, feature embeddings produced by the model encode semantic information in a way reminiscent of word embedding approaches, making them useful for a range of related tasks such as tag recommendations. Subjects: Information Retrieval (cs.IR) ACM classes: B.3.3 Cite as: arXiv:1507.08439v1 [cs.IR] for this version)



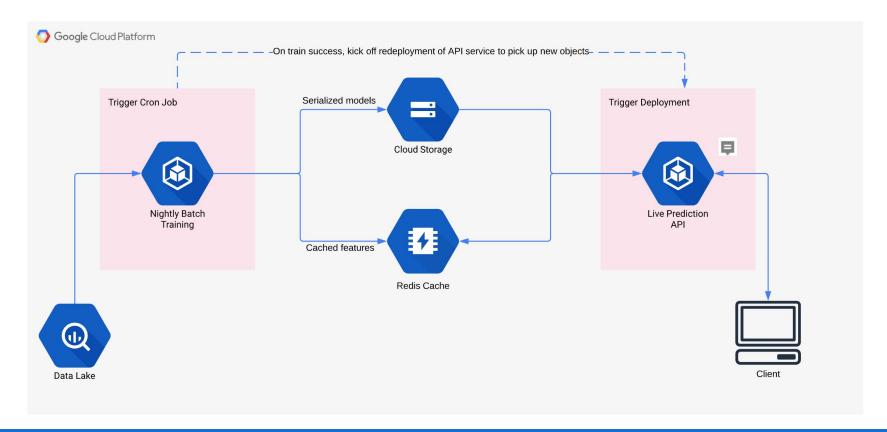


Features:

- Demographics: age, gender...
- Location
- Membership: type...
- Goal / Weight
- Tags, interactions
- Groups

..







Primrose



Taking Stock of our own challenges

What would make a good recommender system at WW?

Slow serialization



but our medium data can be kept in RAM...

No live features



but we know Docker, k8s...

Easy onboarding



mono repo with config as code...



Primrose has features to address each design consideration



Primrose: (*Production In-Memory Solution*) framework for solving WW's most common use cases, caching batched predictions with machine-learning engineering baked-in.

Data science

Python **in-memory DAG** runner, with **no serialization** between nodes of the DAG.

Infrastructure

DAG is defined as **configuration-as-code** approach -- one container for all models

People

Abstract ML and data manipulation operations, data scientists can easily **extend the framework**

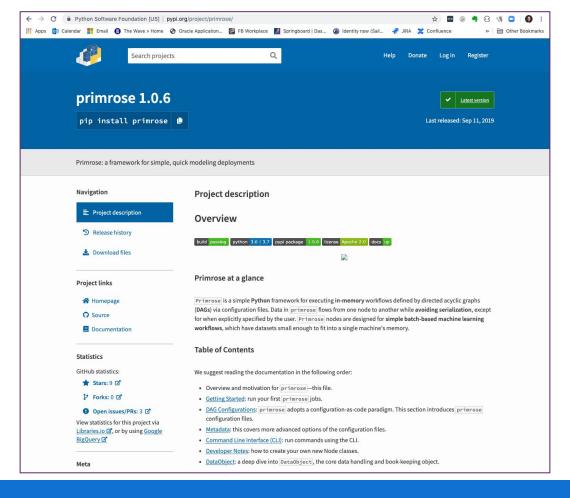


Primrose: a framework for simple, quick modeling deployments



and we open sourced it....



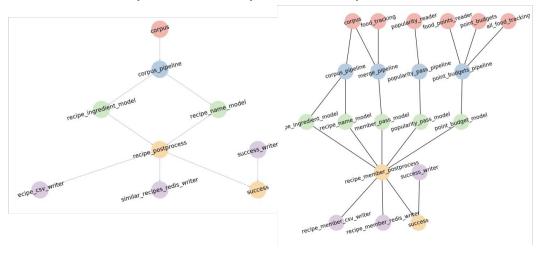




Primrose jobs are executed as Directed Acyclic Graphs (DAG)s in python



Recipe Recommendations

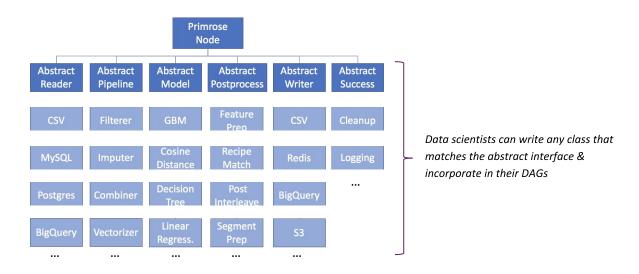


Flexibility: any number of operations allowed in a single DAG, across any python library

Data and functions are passed between nodes in an object that understands how to extract the correct data for each node



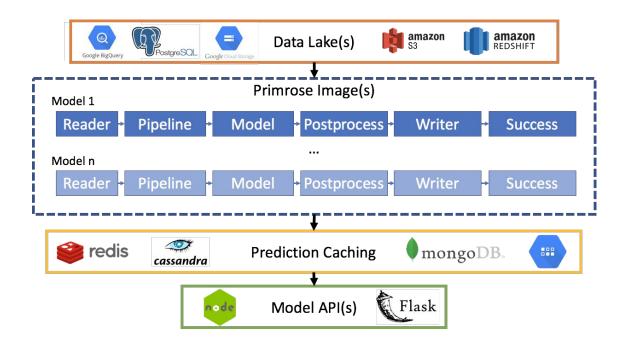
DAGs are composed of implementation agnostic, extensible nodes for data science



Data scientists can write individual nodes using any Python framework or library they choose



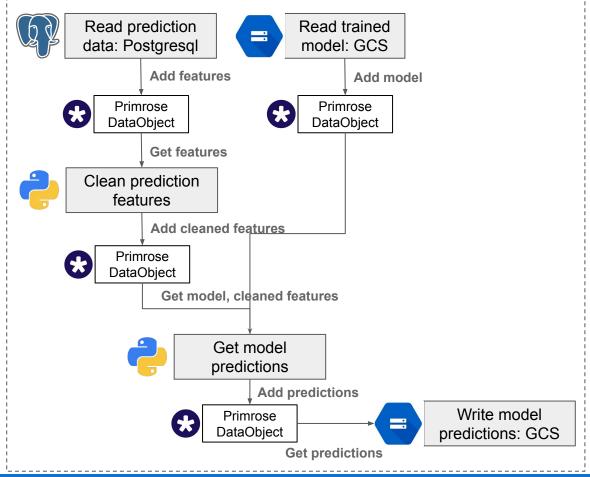
Primrose is run like an ETL pipeline in a single docker container for each configuration





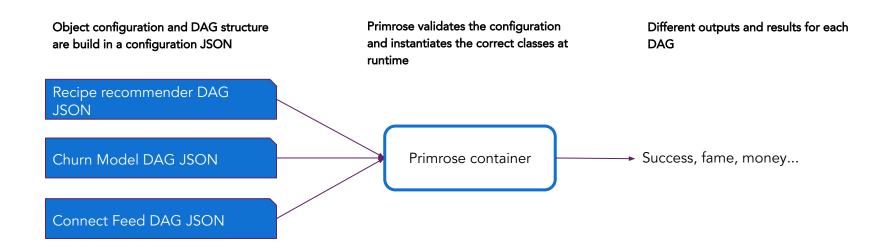


Single Primrose image





For simpler deployments: Primrose uses a "configuration as code" approach





Primrose config snippet: cluster with KMeans

```
"kmeans_cluster_model":{
    "class": "SklearnClusterModel",
    "mode": "train",
    "features": ["x1","x2"],
    "model": {
        "class": "cluster.KMeans",
        "args": {"n_clusters": 6, "random_state": 42}
    },
    "destinations": ["write_data", "write_model"]
}
```

Primrose config snippet: use DBSCAN instead

```
"dbscan_cluster_model":{
    "class": "SklearnClusterModel",
    "mode": "train",
    "features": ["x1","x2"],
    "model": {
        "class": "cluster.DBSCAN",
        "args": {"min_samples": 3}
    },
    "destinations": ["write_data", "write_model"]
}
```

Primrose job in cloud

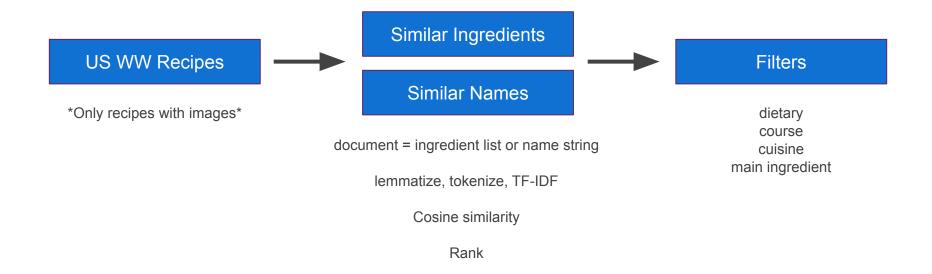


Primrose container

Same container & build!



Similar Recipes Flow





Productionalize in Primrose DAG

```
Google BigQuery Data lake Reader

NLTK + Custom Lemmatization

corpus_pipeline
```

```
"corpus_pipeline": {
    "class": "SimilarRecipesPipeline",
    "nonfood_image_exclude_list": "data/non_food_image_exclude_list.txt",
    "filter_out_non_image": true,
    "remove_dupe_ingredients": true,
    "filter_in_dinner": false,
    "is_training": true,
    "popularity_scaling_min": 0.4,
    "popularity_scaling_max": 0.6,
    "destinations": [
        "ingredient_model",
        "name_model"
]
```

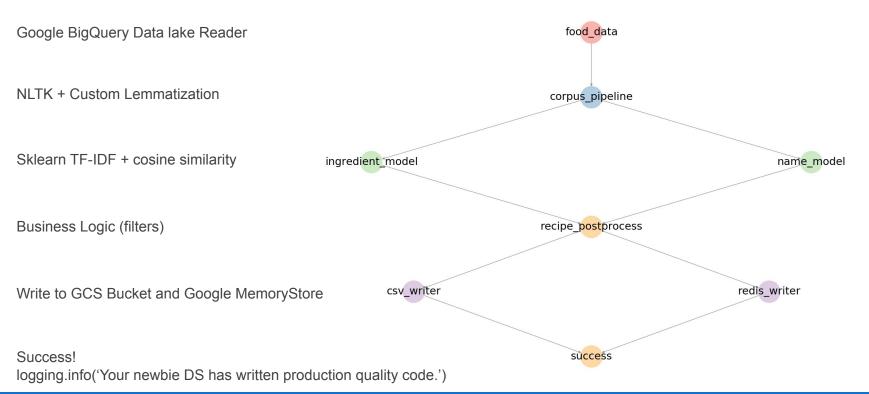


Productionalize in Primrose DAG

food data Google BigQuery Data lake Reader NLTK + Custom Lemmatization corpus pipeline Sklearn TF-IDF + cosine similarity ingredient model name model "corpus pipeline": { "class": "SimilarRecipesPipeline", "nonfood image exclude list": "data/non food image exclude list.txt". "ingredient model": { "name model": { "class": "RecipeIngredientSearchEngine", "filter out non image": true, "class": "RecipeNameSearchEngine", "remove dupe ingredients": true, "mode": "predict", "mode": "predict", "filter in dinner": false, "id_key": "recipeID", "id kev": "recipeID". "is training": true. "doc key": "ingredient string", "doc key": "displayName", "popularity scaling min": 0.4, "destinations": ["destinations": ["popularity scaling max": 0.6, "recipe postprocess" "recipe postprocess" "destinations": ["ingredient model", "name model"

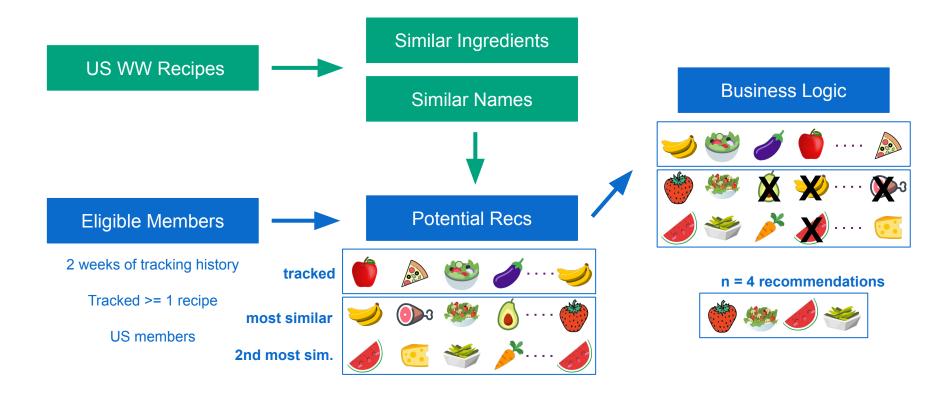


Productionalize in Primrose DAG



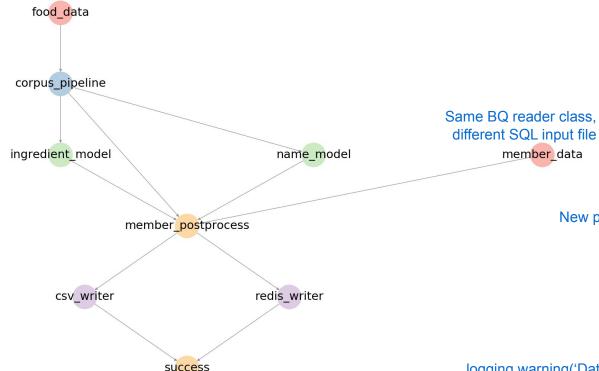


Dinner Recommendations Flow





Productionalizing is easier the second time



New postprocess class to sort, filter and interleave potential recommendations

```
"member_postprocess": {
   "class": "RecipeMemberPostprocess",
   "destinations": [
    "csv_writer",
    "redis_writer"
]
```

Success!

logging.warning('Data Scientist is developing software engineering skills.')



Primrose has features to address each design consideration



Primrose: (*Production In-Memory Solution*) framework for solving WW's most common use cases, caching batched predictions with machine-learning engineering baked-in.

Data science

Python **in-memory DAG** runner, with **no serialization** between nodes of the DAG.

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DAG is defined as **configuration-as-code** approach -- one container for all models

People

Abstract ML and data manipulation operations, data scientists can easily **extend the framework**



Wrap Up

Nudges:

- Once is not enough: nudge different times, channels, timescales
- Recognition really important: Nudge before, recognize after
- Holistic view: challenges, community, personality

Primrose:

- In-memory, config-as-code, extensible
- Helped our new team be productive and get models into prod
- Available today



Questions

- <u>carl.anderson@ww.com</u>
- @leapingllamas
- Food RecSys: https://arxiv.org/abs/1809.02862
- Primrose: https://github.com/ww-tech/primrose

Tech blog: https://medium.com/ww-tech-blog

Hiring: especially data scientists in Toronto

