HOW AI WILL CHANGE MARKETING FOREVER

Christopher S. Penn
Co-Founder, BrainTrust Insights
BrainTrustInsights.com | @TrustInsights
Christopherspenn.com | @cspenn

#Next10x

NEXT10X

brain+trust
INSIGHTS

V

V

V

V

VOLUME

∨
∨
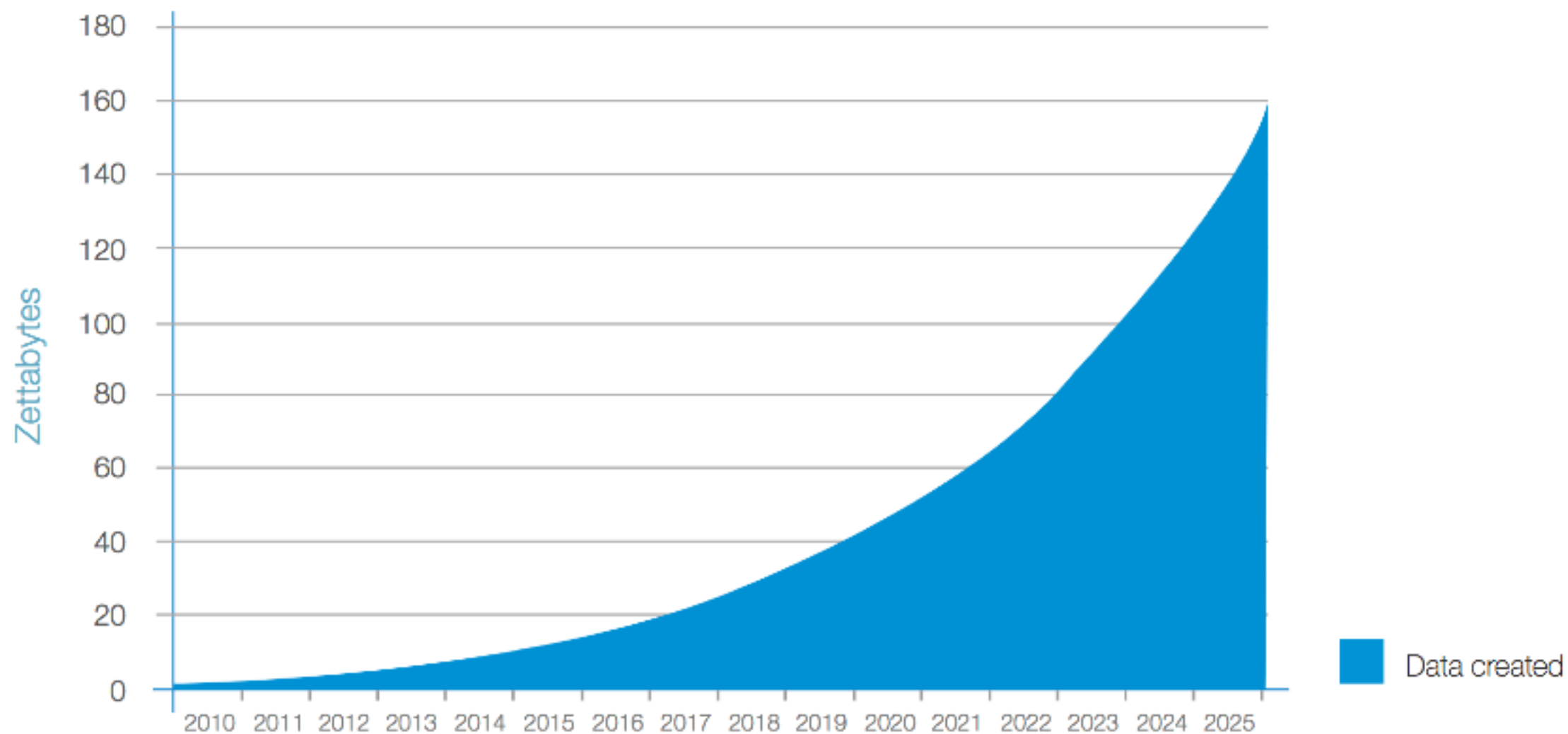## ∨

Figure 2. | Annual Size of the Global Datasphere

Source: IDC's Data Age 2025 study, sponsored by Seagate, April 2017

If each gigabyte in a zettabyte were a brick, we would build 14 Great Walls of China a day.

VARIETY
V
V

2017 This Is What Happens In An Internet Minute

facebook — 900,000 Logins
16 Million Text Messages
YouTube — 4.1 Million Videos Viewed
Google Play / App Store — 342,000 Apps Downloaded
Google — 3.5 Million Search Queries
Instagram — 46,200 Posts Uploaded
NETFLIX — 70,017 Hours Watched
452,000 Tweets Sent
$751,522 Spent Online
990,000 Swipes — tinder
1.8 Million Snaps Created
156 Million Emails Sent
15,000 GIFs Sent via Messenger
40,000 Hours Listened — Spotify
120 New Accounts Created — Linked in
50 Voice-First Devices Shipped — amazon echo

60 SECONDS

Created By:
@LoriLewis
@OfficiallyChadd

2018 This Is What Happens In An Internet Minute

facebook — 973,000 Logins
18 Million Text Messages
YouTube — 4.3 Million Videos Viewed
Google Play / App Store — 375,000 Apps Downloaded
Google — 3.7 Million Search Queries
Instagram — 174,000 Scrolling Instagram
NETFLIX — 266,000 Hours Watched
481,000 Tweets Sent
$862,823 Spent Online
1.1 Million Swipes — tinder
2.4 Million Snaps Created
187 Million Emails Sent
25,000 GIFs Sent via Messenger
38 Million Messages — WhatsApp
67 Voice-First Devices Shipped — amazon echo
936,073 Views — twitch

60 SECONDS

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VOLUME

VARIETY

VELOCITY

V

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Total Google News Stories Per Year by URL Count

Sqldate

On track for about 100 million news stories in 2018

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@TrustInsights | BrainTrustInsights.com

Year	Value
1979	430,941
1980	561,446
1981	678,458
1982	764,325
1983	848,806
1984	873,229
1985	987,942
1986	1,077,047
1987	1,091,590
1988	1,183,220
1989	1,077,466
1990	1,126,957
1991	1,471,086
1992	1,097,338
1993	1,310,741
1994	1,774,666
1995	1,780,524
1996	2,793,232
1997	3,652,082
1998	4,267,872
1999	4,754,487
2000	4,540,506
2001	4,995,943
2002	4,415,923
2003	5,532,338
2004	4,652,307
2005	3,547,723
2006	6,358,755
2007	11,255,703
2008	14,335,211
2009	23,464,598
2010	22,502,301
2011	31,501,556
2012	34,583,089
2013	35,363,407
2014	48,355,296
2015	95,230,369
2016	114,490,642
2017	104,620,044
2018	34,674,934

Sum of F0 for each Sqldate Year.

VOLUME
VARIETY
VELOCITY
VERACITY

NEXT 10X

The Prescription Is Cognitive Marketing

What is Cognitive Marketing?

Marketing that **Learns**

Using **AI & ML** Technologies
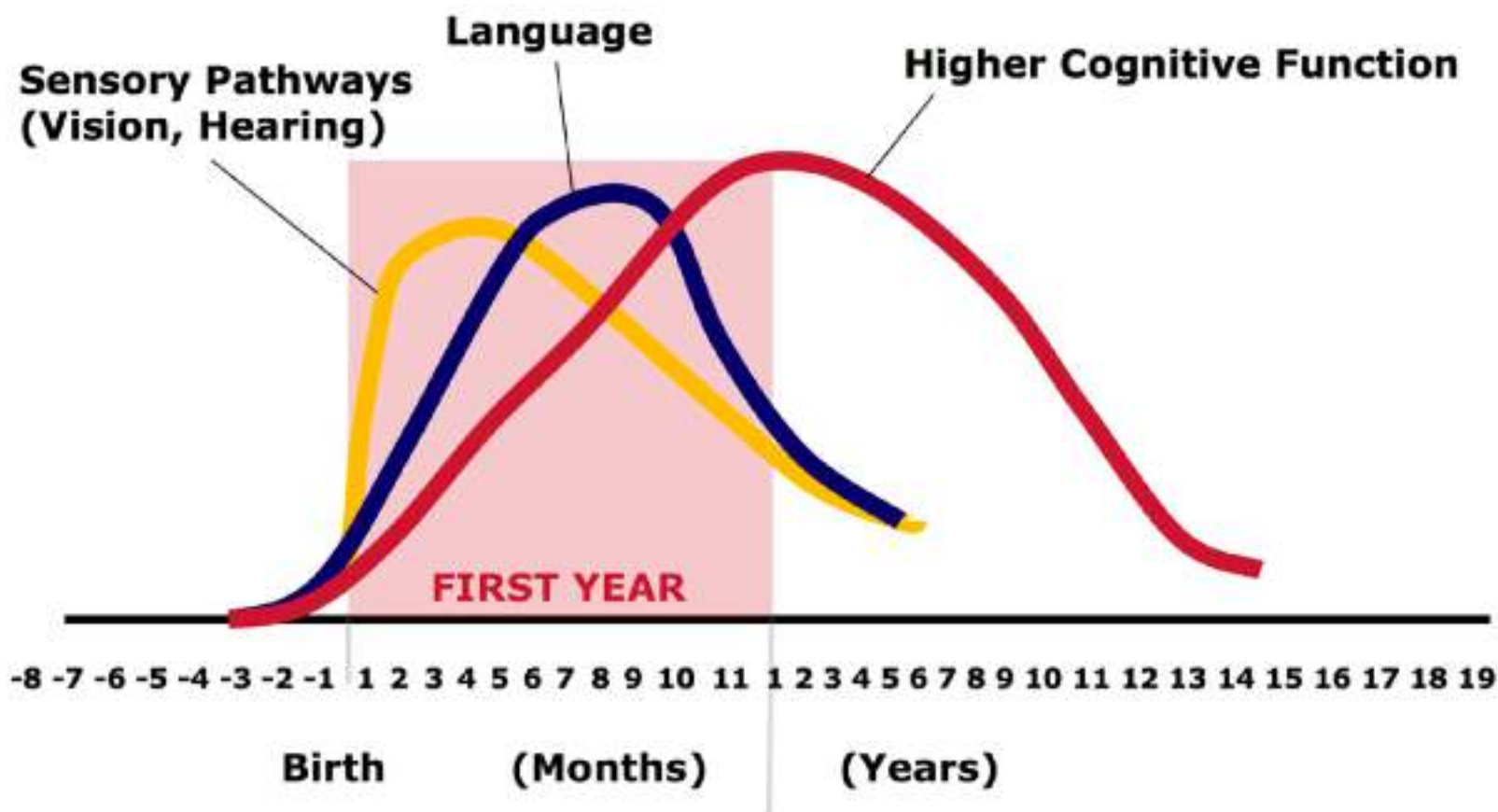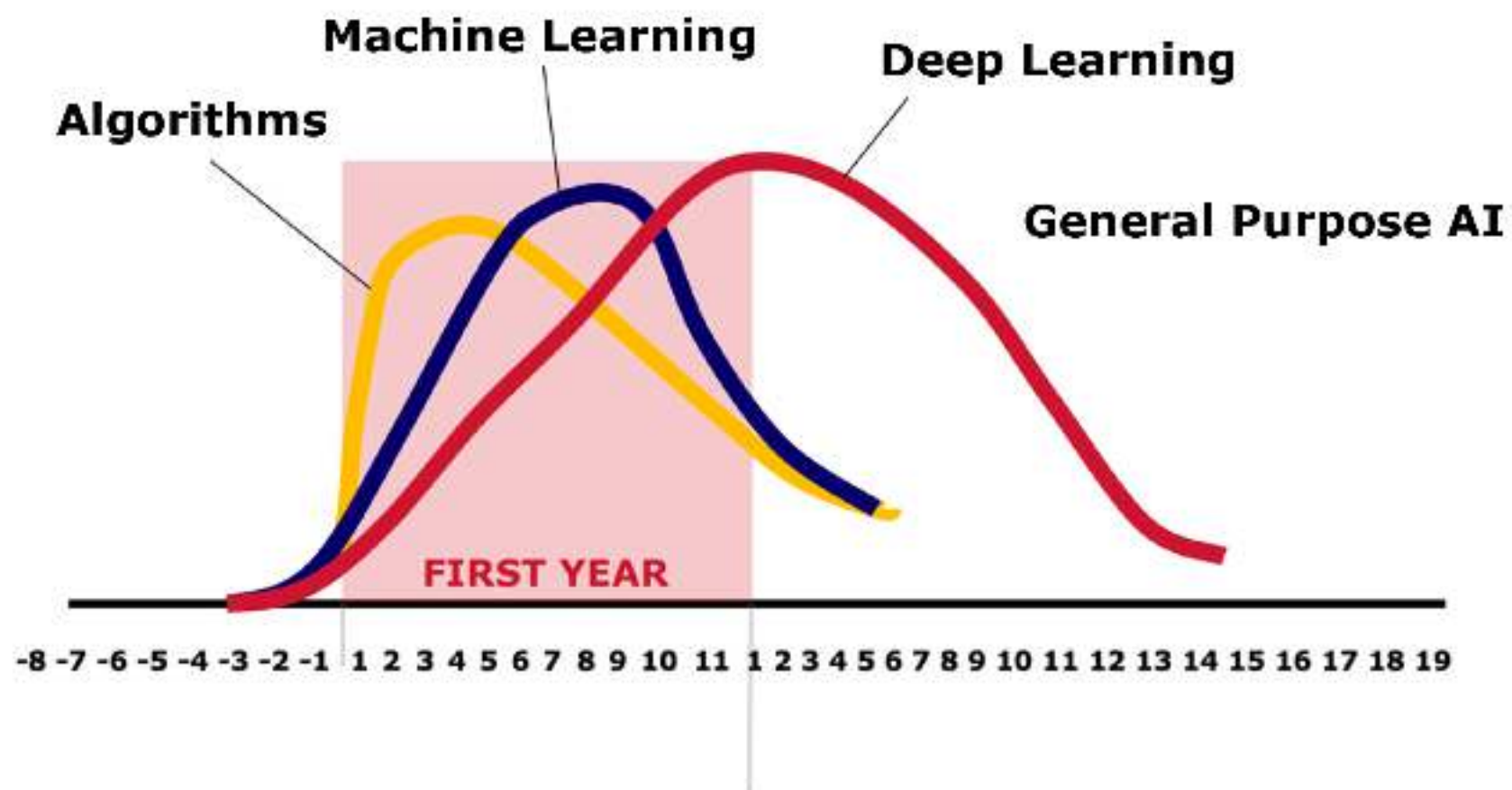
What is Artificial Intelligence?

Where Machine Learning and AI Are Going

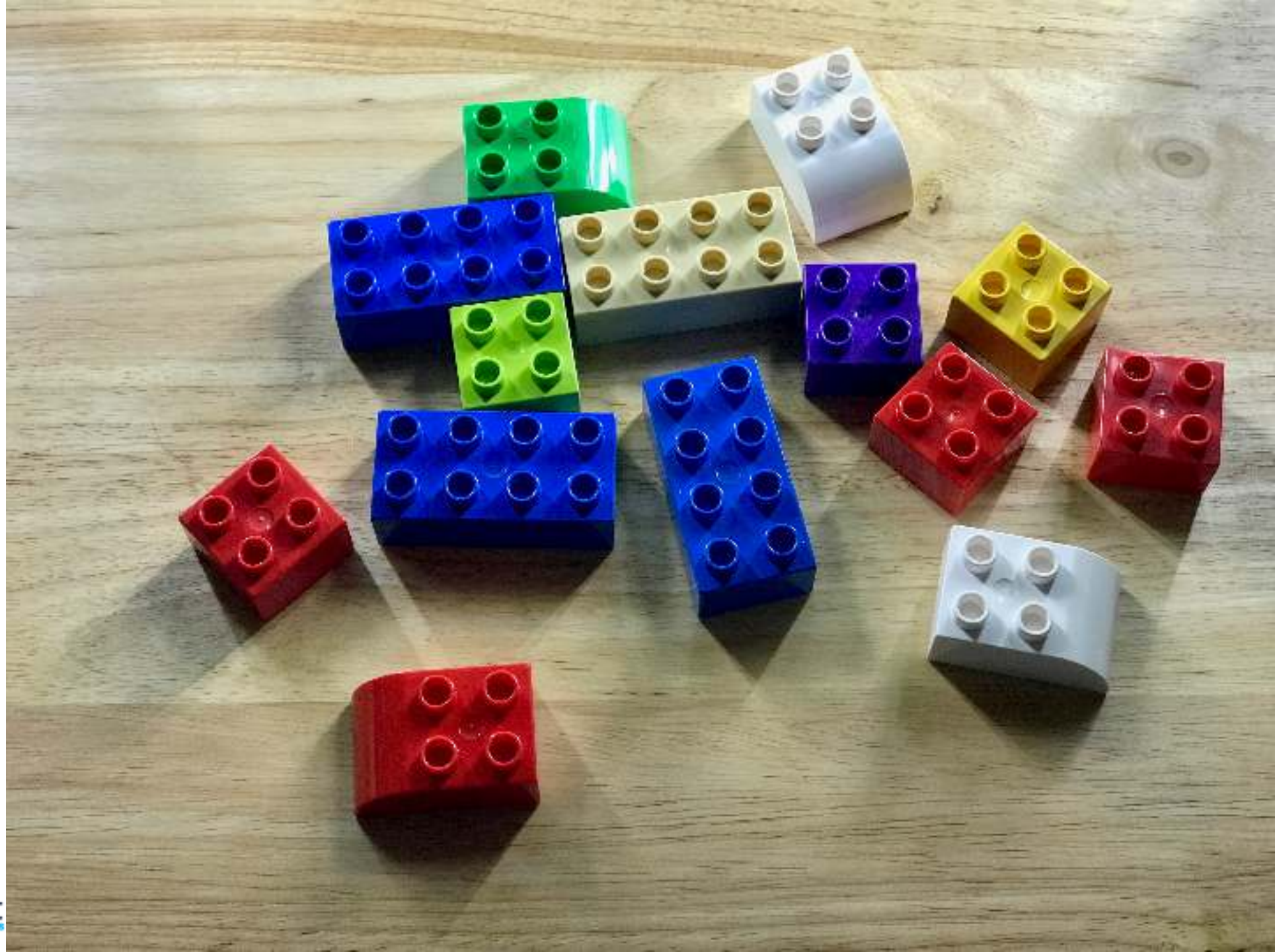Source: C.A. Nelson (2000)

Newsletter Subscription (Goal 1 Completions)

↑ Variant	Improvement	Conversion Rate		Conversions	Experiment Sessions	Probability to beat baseline	Probability to be Best
Original	baseline	6.93% (3.95%, 10.93%)		15	220	baseline	23%
Variant 1: Bigger Popup B...	-15.32% (-61.05%, 80.34%)	5.86% (3.13%, 9.75%)		11	200	33%	10%
Variant 2: Blue Popup Butt...	22.65% (-36.76%, 144.34%)	8.49% (5.25%, 12.71%)		18	221	73%	64%
Variant 3: Blue AND Bigger...	-25.72% (-65.89%, 58.55%)	5.14% (2.73%, 8.57%)		11	228	22%	4%

A/B Split Tests and Multivariate Tests Are Algorithms
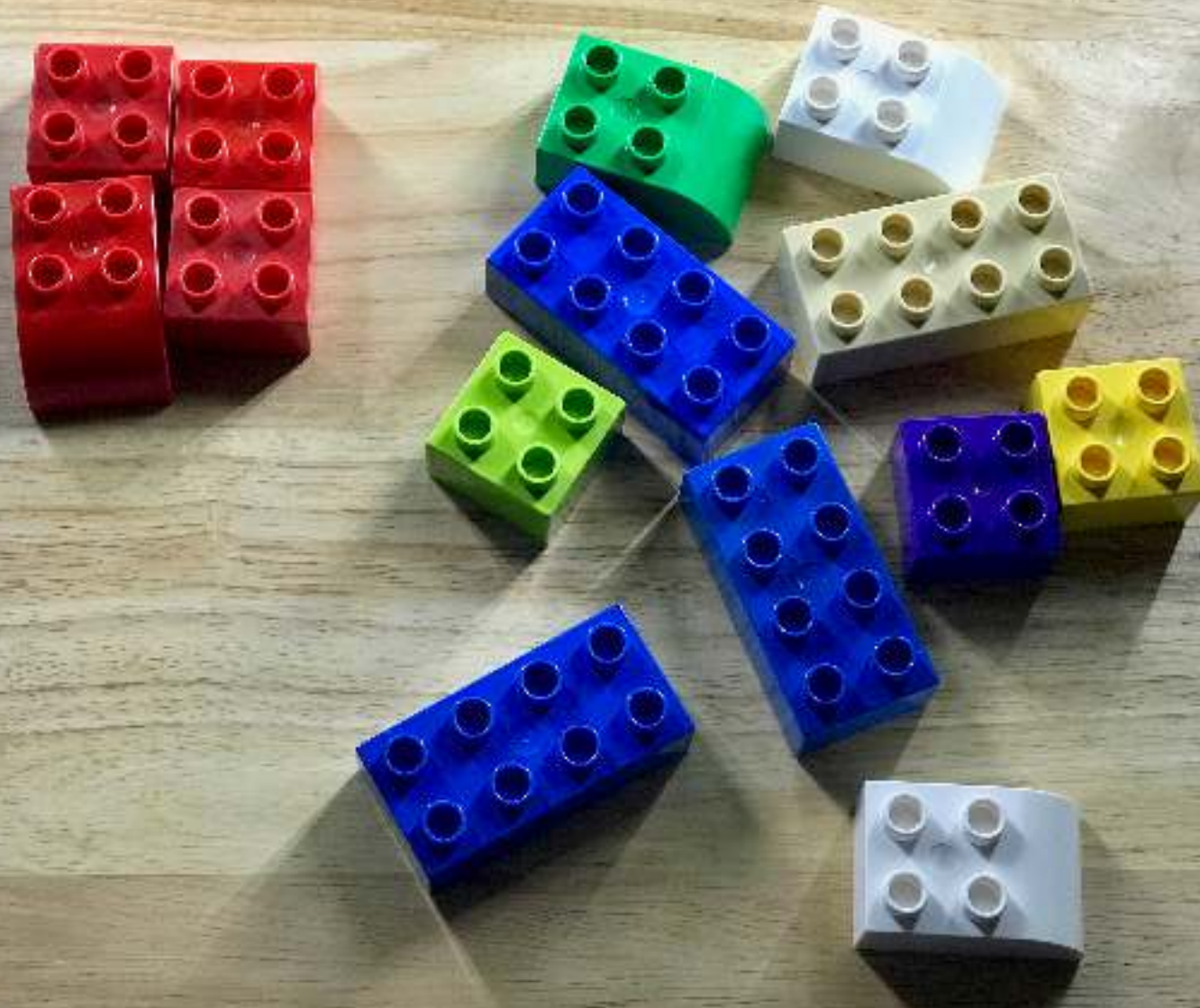
Conversion Rate Over time

Legend:
- Original
- Variant 1: Bigger Popup Button
- Variant 2: Blue Popup Button
- Variant 3: Blue AND Bigger Button
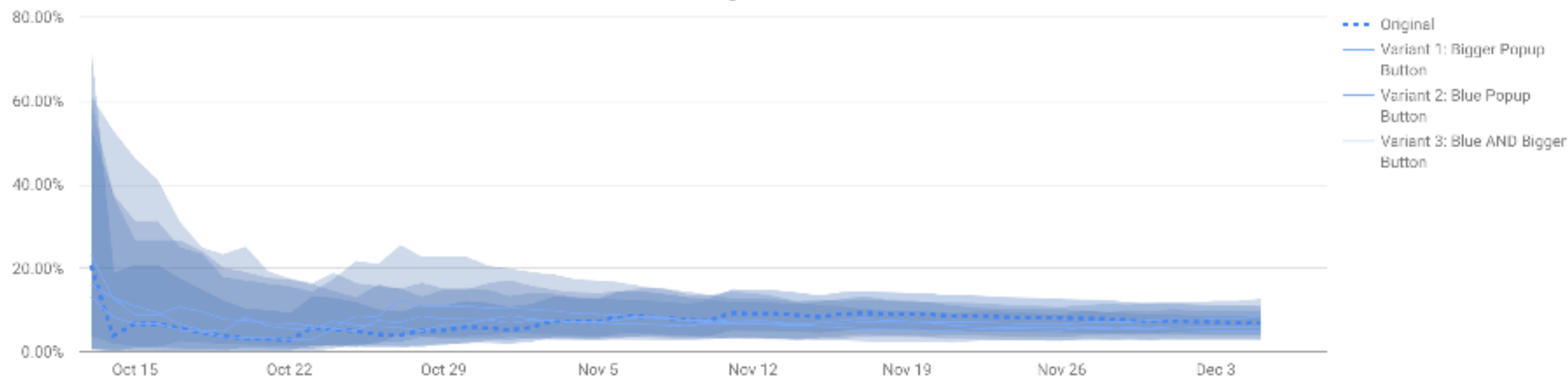
Machine Learning

Supervised Learning

RED

brain+trust
INSIGHTS

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Home   **Patients**   Cohorts   Therapy

Patient List > Raymond Svenson   Patient: Raymond Svenson

🗐 Summary	Azacitidine+PKC412	2010-0374	salvage-1	08/27/2013	Date Not Available

🖾 Timeline	
📊 Current Labs	OEA Suggestions **Approved Therapies** Genomic Based Rx Clinical Trials
▦ Past Labs	

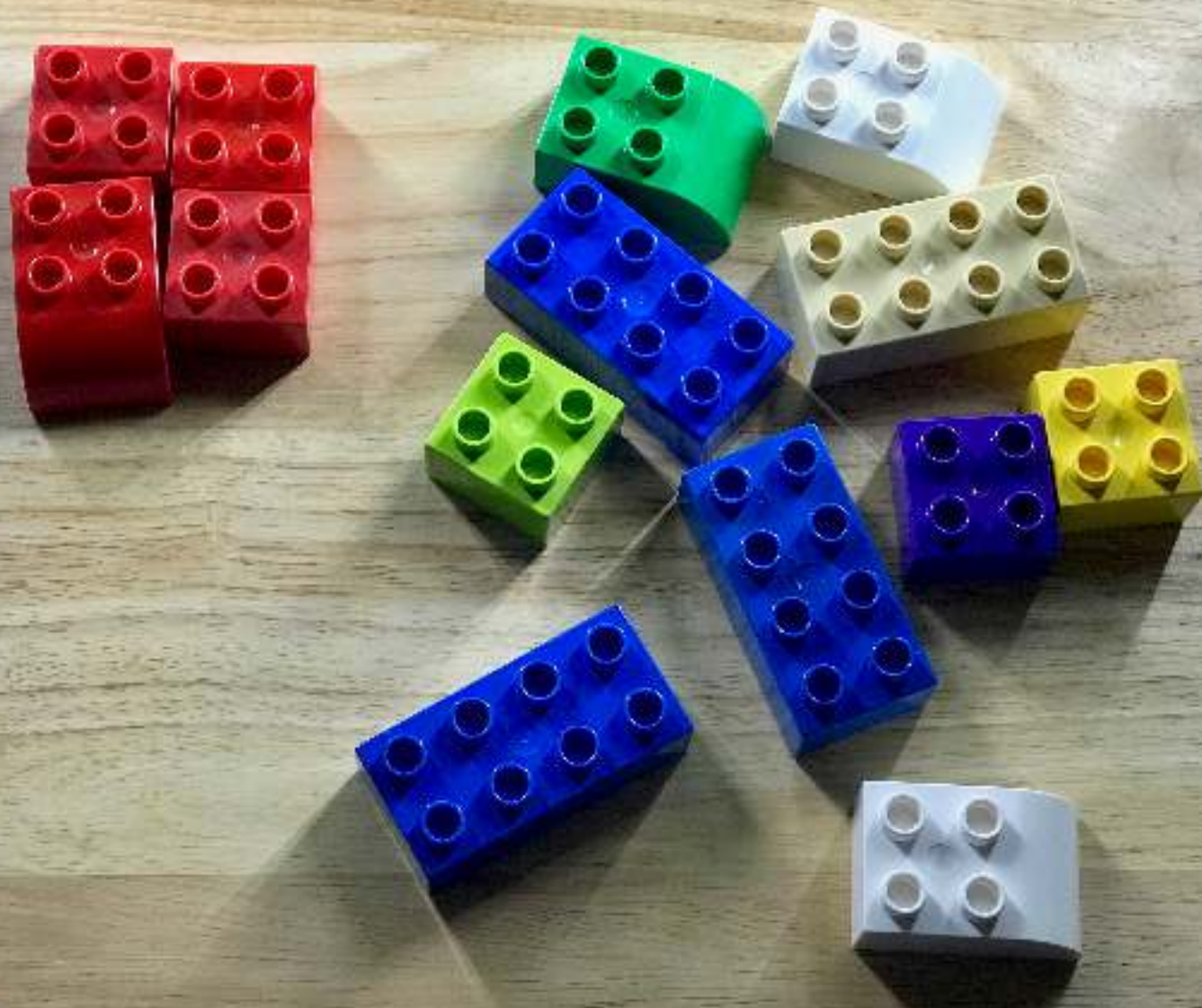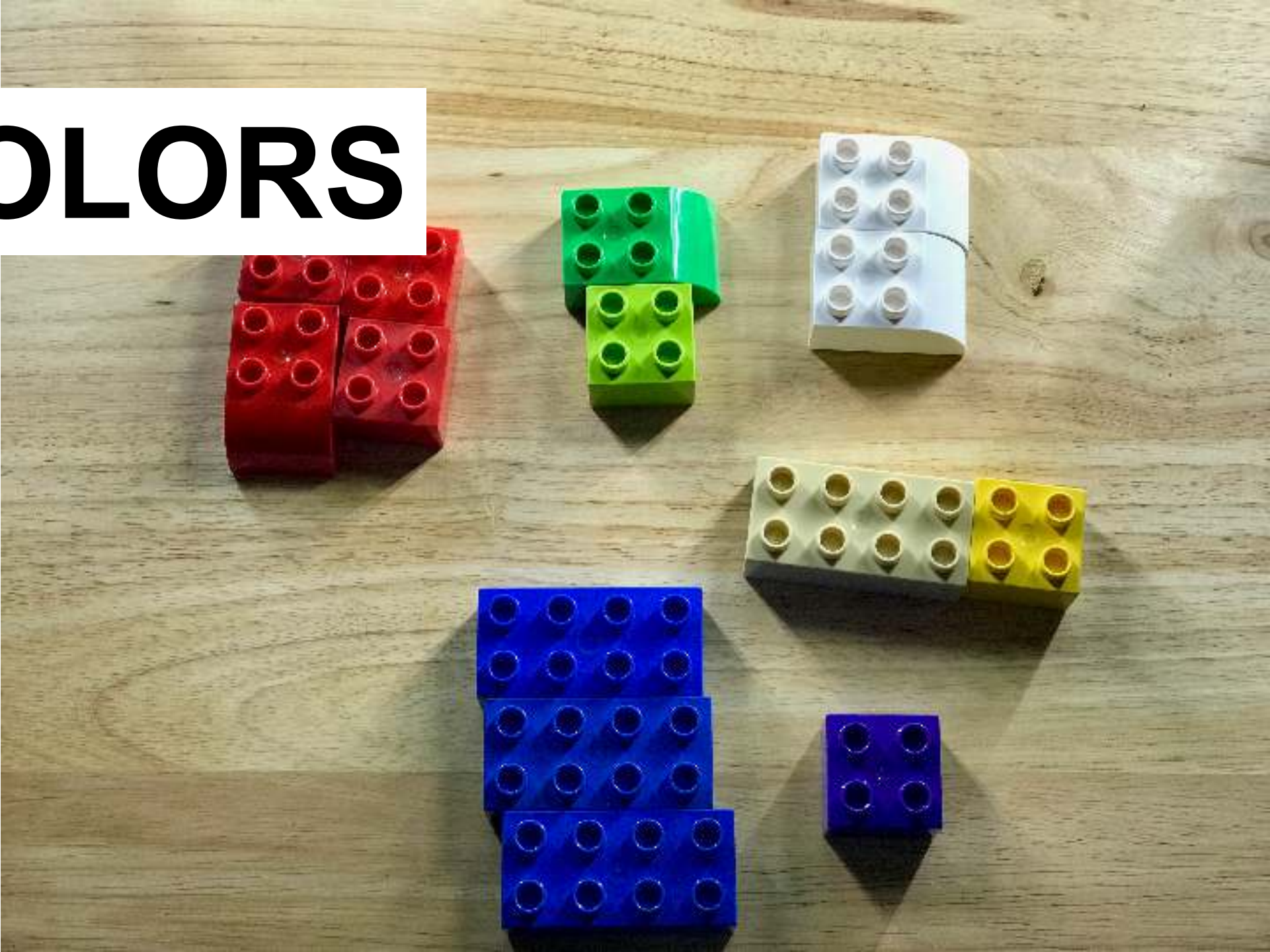| Therapy	Confidence	Audit	Rating
Salvage fludarabine + cytarabine + GCSF +/- idarubicin	▮▮▮▮▮ Very High	Audit	👍 👎 (0 comments)
Salvage clofarabine + cytarabine + GCSF	▮▮▮ Medium	Audit	👍 👎 (0 comments)
Subcutaneous Cytarabine, 5-azacytidine, Decitabine	▮▮▮ Medium	Audit	👍 👎 (0 comments)
Salvage cladribine + cytarabine + GCSF +/- mitoxantrone or idarubicin	▮▮▮ Medium	Audit	👍 👎 (0 comments)
Salvage HiDAC +/- anthracycline	▮▮▮ Medium	Audit	👍 👎 (0 comments)
Intermediate-intensity therapy (clofarabine)	▮▮▮ Medium	Audit	👍 👎 (0 comments)
Standard-dose Cytarabine 100-200, Idarubicin 12 or Daunorubicin 45-90 or Mitoxantrone 12	▮▮▮ Medium	Audit	👍 👎 (0 comments)
Salvage etoposide + cytarabine +/-	▮▮▮▮▮ Low	Audit	👍 👎 (0 comments)

Side navigation: Prognosis, Latest Therapy, Therapy History, **Suggested Therapies**, Patient Similarities

Unsupervised Learning

RED

COLORS

SHAPES

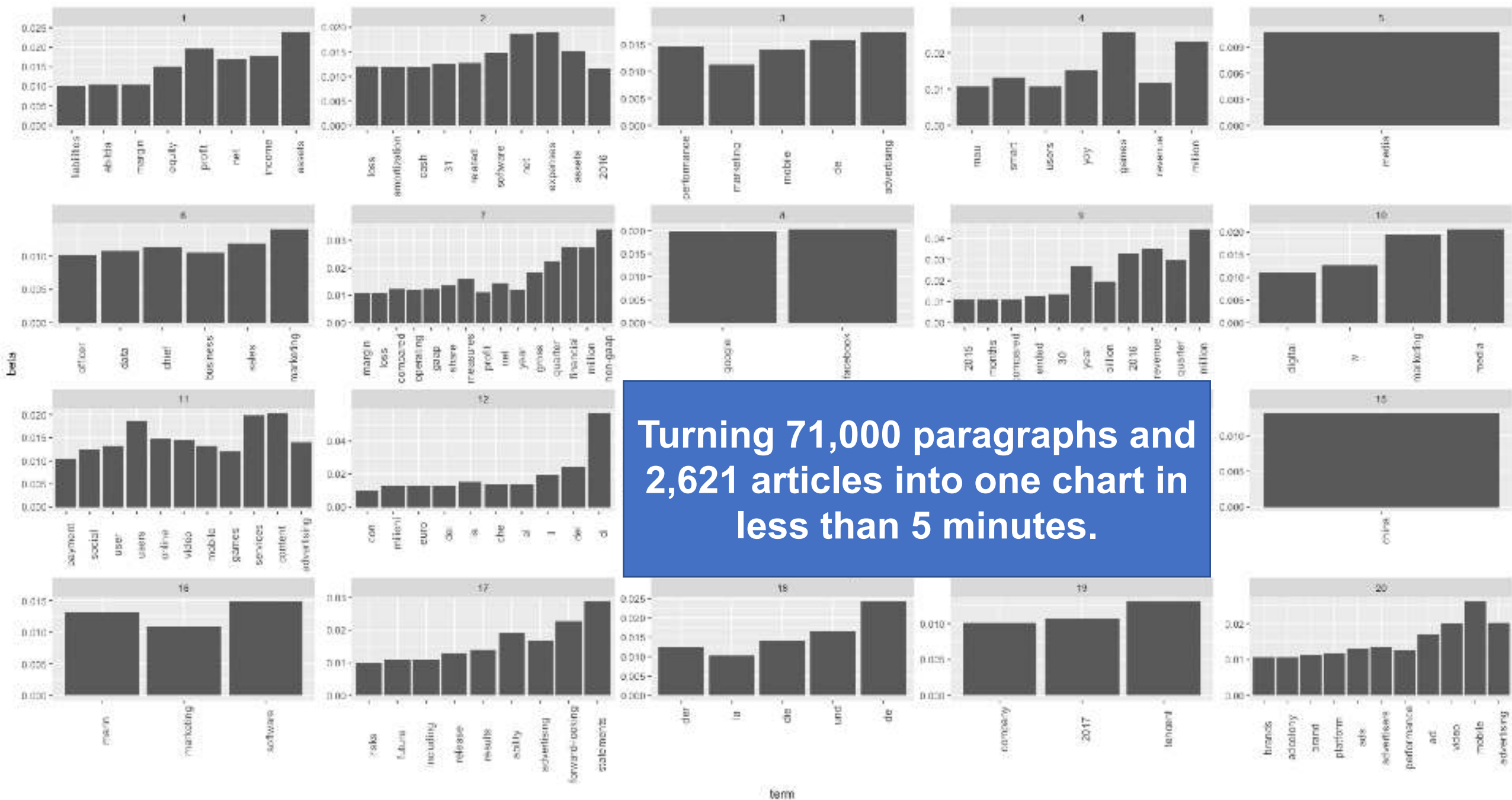**Turning 71,000 paragraphs and 2,621 articles into one chart in less than 5 minutes.**

Machine Learning
is Mostly Math & Statistics

Example Machine Learning Techniques:

Clustering Algorithms
Decision Trees
Ensemble Methods
Independent Component Analysis
K-means
Linear Regression
Logistic Regression
Naïve Bayes Classification
Ordinary Least Squares Regression
Principal Component Analysis
Random Forests
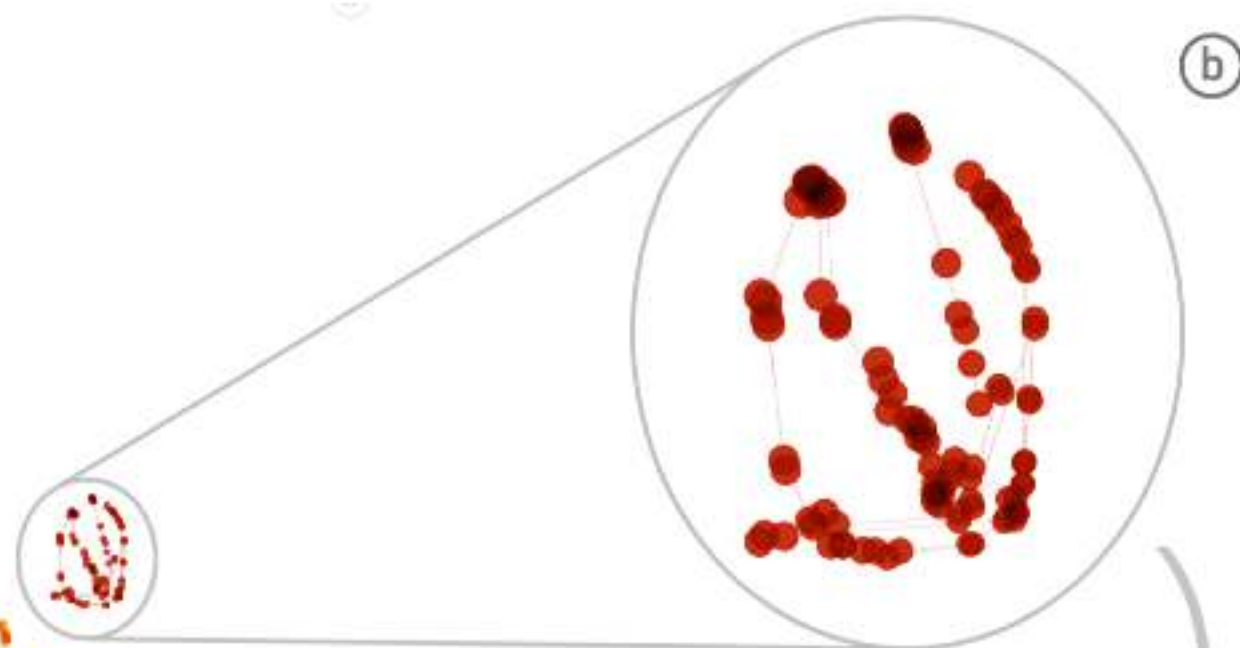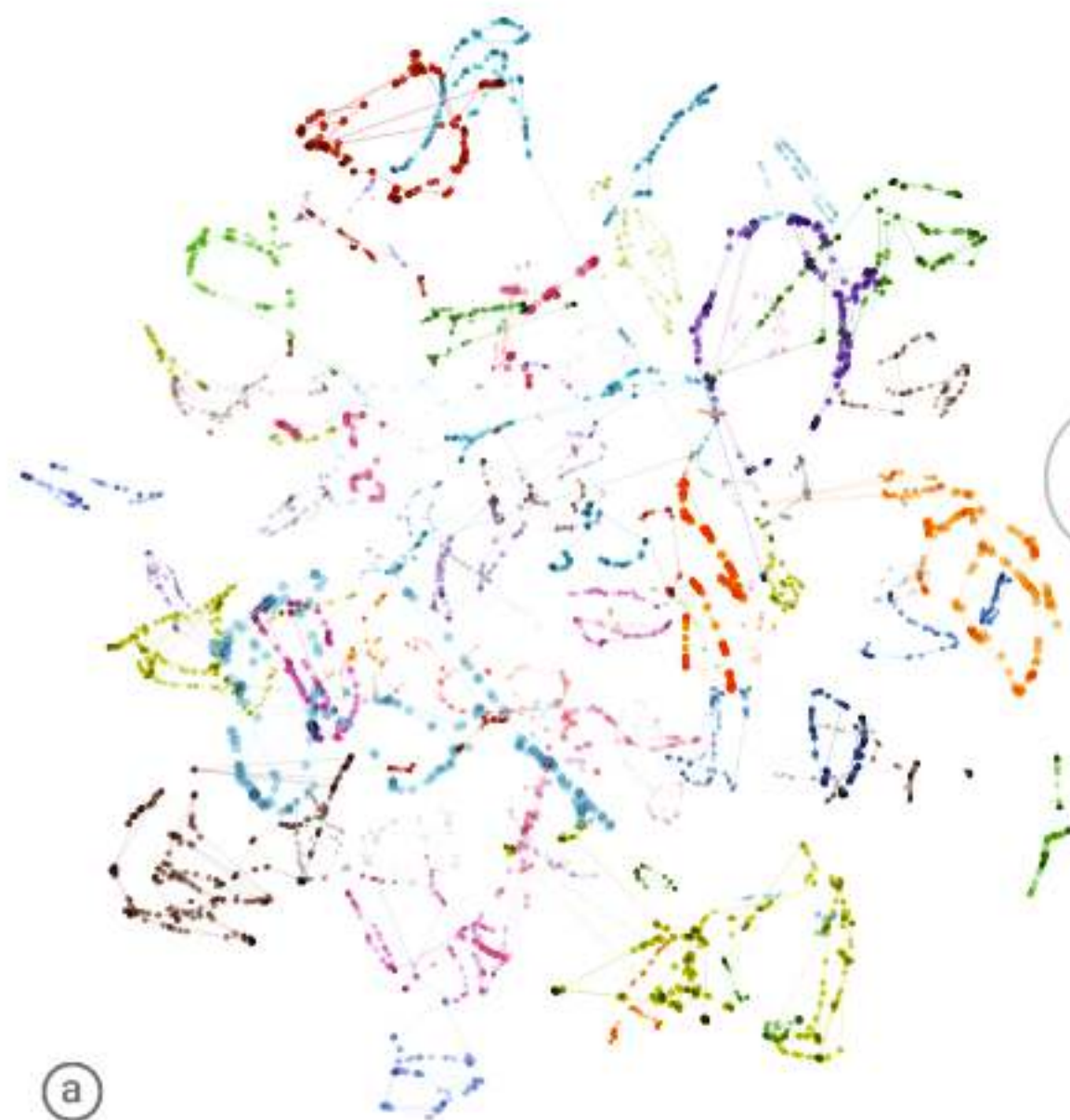Singular Value Decomposition
Support Vector Machines

http://www.kdnuggets.com/2016/08/10-algorithms-machine-learning-engineers.html

Deep Learning

Many Layers of Machine Learning

=

Deep Learning

Machines that think like us
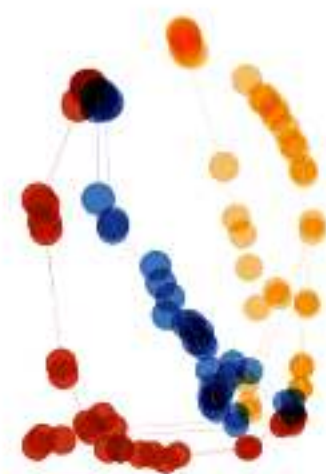
faster

… only better

cheaper

(a)

(b)

(c)

ENGLISH

The stratosphere extends from about
10km to about 50km in altitude.

KOREAN

성층권은 고도 약 10km부터 약
50km까지 확장됩니다.

JAPANESE

成層圏は、高度 10km から
50km の範囲にあります。

Where Machine Learning and AI Are Not Going

How Do We Use AI in Marketing Now?

Foundation

Markov Chain Model - Attribution by Goal Value - All Goals

Channelname

Channelname	Value
ActiveCampaign/email	6,468
disq.us/referral	6,031
google/organic	5,253
t.co/referral	3,683
linkedin.com/referral	2,837
medium.com/referral	2,776
twitter/social	2,502
twitter.com/social	2,462
armentdietrich.com/referral	2,093
nutspr.com/referral	1,451
facebook/cpc	1,258
linkedIn/social	1,237
twitter/SpinSucks	934
bing/organic	856
yahoo/organic	813
facebook.com/referral	554
fbads/facebookads	480
mail.google.com/referral	401
deirdrebreakenridge.com/referral	382
plus.google.com/social	347
business.facebook.com/referral	346
twitter/ginidietrich	296
facebookads/referral	291
contributedposts/blogpost	258
linkedin.com/social	227
l.facebook.com/referral	195
feedly.com/referral	182
socialracemedia.com/referral	169

Value

Attribution

Fixing LinkedIn Shares

Connection

Understanding

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
3.06%	2.86%	2.35%	1.59%	1.49%	1.31%	1.06%	1.00%	0.94%	0.81%
marketing	consumer	marketing	business	products	lesson	product	worksheet	search	ago
definition	markets	content	marketing	businesses	courses	service	industry	brands	days
business	business-to-business	advertising	marketers	services	custom	terms	specific	online	hours
examples	market	social	customers	consumers	lessons	marketing	news	marketing	account
strategies	decision	digital	brand	buy	share	policy	buyers	social	marketingb
strategy	business	business	page	product	account	technology	materials	internet	marketingverified
research	target	social_media	importance	consumer	learn	cart	life	content	boston
degree	purchase	success	relationships	companies	video	privacy	names	investment	rights
review	companies	facebook	management	sell	tweet	segment	world	mind	reserved
consumer	marketing	media	sale	purchase	college	require	multiple	white	human
overview	customers	companies	security	quality	add	technical	authors	research	media
sales	products	goal	customer	level	start	price	common	companies	international
customer	key	platforms	branding	tend	study	office	list	return	turn
content	buying	sales	potential	single	people	offering	company	papers	means
principles	marketers	trade	current	food	exams	provided	standards	heering	hotel
process	transactions	channels	lead	business	free_trial	offer	raw	selling	hotel
services	marketer	reach	technical	grocery	plan	benefits	skills	experience	waterfront
techniques	segments	brand	strategic	customers	create	support	research	social media	westin
business-to-business	individual	company	focused	customer	million	market	transaction	events	abbott
types	buyers	promotion	develop	salesperson	reply	services	marketing	efforts	entrepreneur
automation	edit	world	clients	expertise	access	billingintervaltype	quiz	optimization	profile
information	price	businesses	executives	purchasing	cancel	yyyy	maint	consumers	follow
distribution	consumers	campaign	trust	required	page	flashcards	relationship	sites	sales
consumers	emotional	instagram	issues	rebuy	content	organization	legal	direct	decision
behavior	largest	engage	team	stores	exam	reviews	party	requires	worker

Reverse- Engineering Google

```
[text256, 6]              , salad,  | breadsticks |  , and sometimes
[text259, 17]            salad, and | breadsticks | will run a
[text302, 64]         like putting 6 | breadsticks | in a basket
[text318, 69]      unlimited salads, | breadsticks |  , and soups
[text351, 160]        They also get | breadsticks |  . As many
[text371, 21]            salad, and | breadsticks |  . Hard work
[text377, 37]    endless soup salad | breadsticks |  , just to
[text381, 4]        Soup salad and | breadsticks | are the worst
[text389, 8]            - drinks,  | breadsticks |  , soups,
[text514, 16]            salad, and | breadsticks |  . There are
[text532, 43]          Salad, and | Breadsticks | ( lunch promotion
[text552, 24]            , soups,  | breadsticks |  , and pasta
[text583, 4]        Soup salad and | breadsticks | is a hassle
[text712, 26]  one time.The endless | breadsticks | and salad is
[text712, 43]          You are a  | breadsticks | slave and a
[text726, 8]            soup, and  | breadsticks | sucks
```
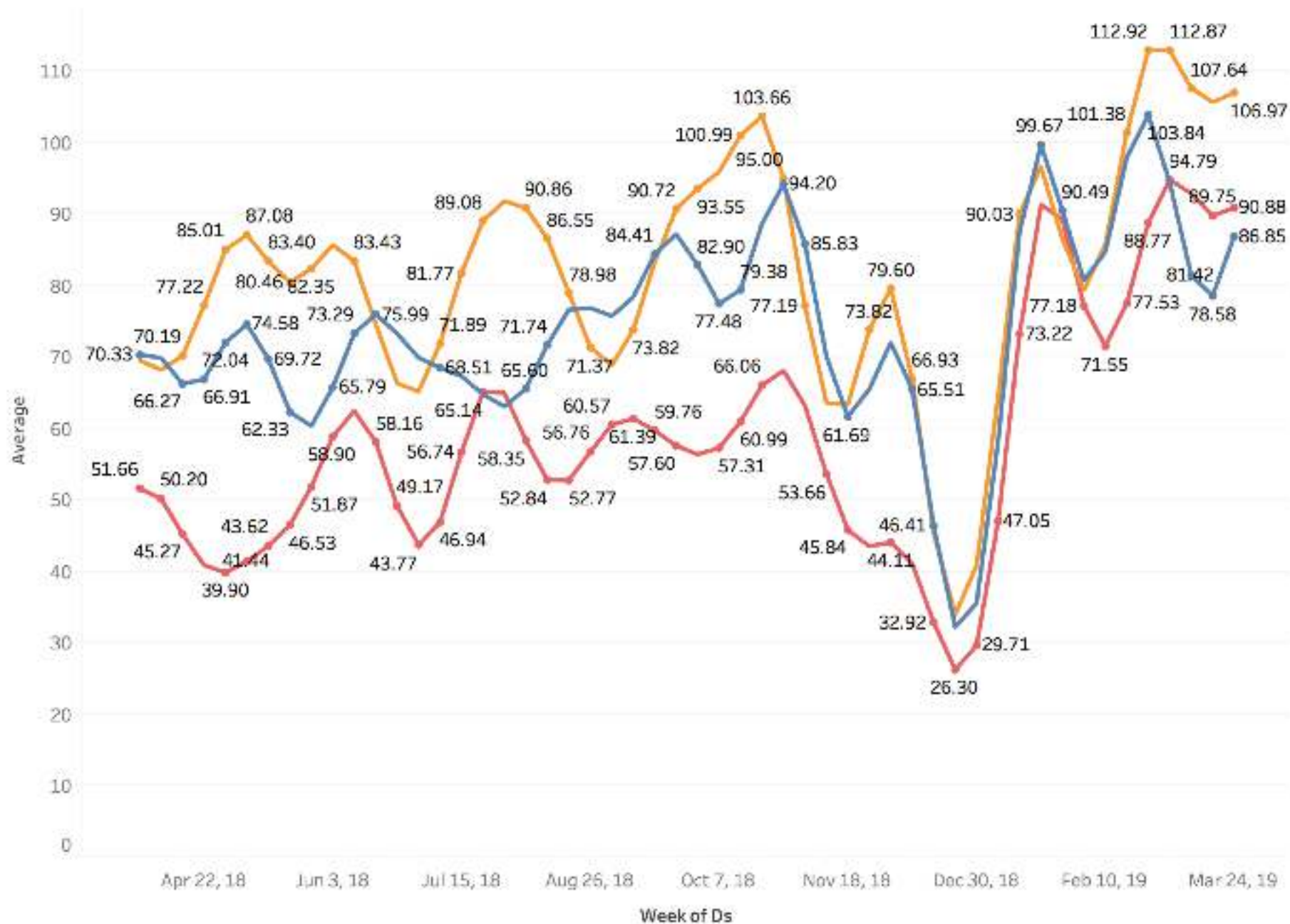
Prediction

Brain+Trust Insights : GitLab Predictive Forecast - Expires 30 April 2018

Campaign Forecast

Week of Ds	marketing-courses	media-training	pr-courses	Group pr-training	public-relations-cour..	social-media-courses	social-media-training
April 8, 2018	76.93			52.48		55.08	55.21
April 15, 2018	62.67						56.63
April 22, 2018	56.67	64.20					60.25
April 29, 2018	56.99	77.68					59.96
May 6, 2018	55.45	70.03			62.00		53.95
May 13, 2018	50.78						
May 20, 2018	50.03						
May 27, 2018	56.92						59.80
June 3, 2018	63.86	56.83					71.60
June 10, 2018	58.21	76.60					75.25
June 17, 2018		75.22					68.38
June 24, 2018		57.99					57.91
July 15, 2018	61.76	62.76					
July 22, 2018	63.31	78.87				57.90	
July 29, 2018	53.69	85.38				63.43	58.83
August 5, 2018		80.93				60.57	74.46
August 12, 2018		71.89				57.91	82.54
August 19, 2018	54.78	64.05				58.96	74.56
August 26, 2018	58.00	60.66			54.63	58.94	59.79
September 2, 2..	57.63	63.20			57.40	53.79	52.88
September 9, 2..	59.20	70.03		54.43			59.24
September 16, ..	65.09	74.88					73.82
September 23, ..	71.25	71.66				55.13	83.03
September 30, ..	73.62	63.44				60.82	79.07
October 7, 2018	75.35	60.12		56.64		59.99	70.86
October 14, 20..	81.75	67.49		58.80		59.28	69.17
October 21, 20..	89.44	80.27				68.82	73.97
October 28, 20..	85.45	83.36				87.09	76.19

How Will AI Change Marketing's Future?

Fewer Humans Needed

EMERGING TECH

Coca-Cola Wants to Use AI Bots to Create Its Ads

Algorithms can already pick music and write copy

By Lauren Johnson | February 28, 2017

If you do it with a template today, a machine does it without you tomorrow. - @cspenn

Faster Marketing

Hyper-Personal Marketing

PERSONA OF ONE

The forecast calls for baking up one-of-a-kind fun with Country Crock® and Watson.

Mix up favorite flavors and ingredients. Stir in imagination.
Create new cookie recipes everyone will love.

Watson invented **Sriracha Cookie** with sriracha, granulated sugar, vanilla extract, frosting, white chocolate chips, chocolate chips, Country Crock® Original buttery spread, flour, egg

MADE WITH

Country Crock® Original buttery spread

GET A COUPON

Like Recipe? Y N

Watson inventions are not kitchen tested.
Please use your judgment and remain mindful of your food preferences and allergies.

Ingredients	Preparation
• ½ cup sriracha	• chocolate chips
• ¾ cup granulated sugar	• ½ cup Country Crock® Original buttery spread
• 1 tsp vanilla extract	• 3 cup flour
• 1¼ cup frosting	• 1 egg
• ¾ lb white chocolate chips	

Higher Barriers to Entry

START NOW

M
A
G
I

Microsoft
Cognitive Services

amazon
web services

Google Cloud Platform

IBM BlueMix

brain+trust
INSIGHTS

NEXT 10X

Machine Learning Languages to Start With

How to Prepare Your Career for AI

Multidisciplinary Skills

The 10 most in-demand hard skills in 2018 via LinkedIn

1. Cloud and Distributed Computing
2. Statistical Analysis and Data Mining
3. Middleware and Integration Software
4. Web Architecture and Development Framework
5. User Interface Design
6. Software Revision Control Systems
7. Data Presentation
8. SEO/SEM Marketing
9. Mobile Development
10. Network and Information Security

Algorithmic Thinking

Learn to think like a machine
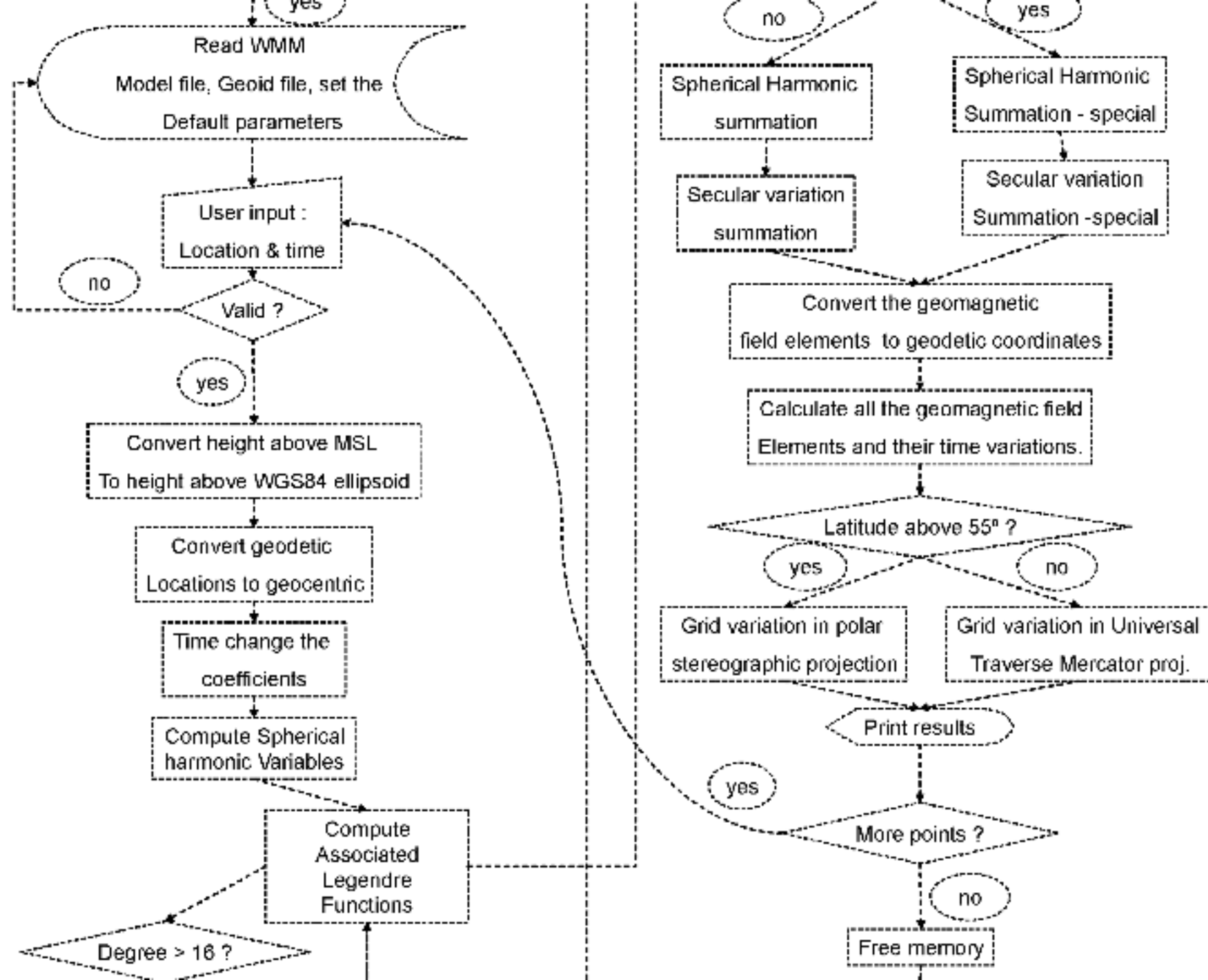
Machine **Oversight**

Outcome-Focused

Deep Learning with Keras : : **CHEAT SHEET**

Intro

Keras is a high-level neural networks API developed with a focus on enabling fast experimentation. It supports multiple backends, including TensorFlow, CNTK and Theano.

TensorFlow is a lower level mathematical library for building deep neural network architectures. The keras R package makes it easy to use Keras and TensorFlow in R.

Define → **Compile** → **Fit** → **Evaluate** → **Predict**

- Define
  - Model
  - Sequential model
  - Multi-GPU model
- Compile
  - Optimiser
  - Loss
  - Metrics
- Fit
  - Batch size
  - Epochs
  - Validation split
- Evaluate
  - Evaluate
  - Plot
- Predict
  - classes
  - probability

https://keras.rstudio.com

https://www.manning.com/books/deep-learning-with-r

The "Hello, World!" of deep learning

Working with keras models

DEFINE A MODEL

keras_model() Keras Model

keras_model_sequential() Keras Model composed of a linear stack of layers

multi_gpu_model() Replicates a model on different GPUs.

COMPILE A MODEL

compile(object, optimizer, loss, metrics = NULL) Configure a Keras model for training

FIT A MODEL

fit(object, x = NULL, y = NULL, batch_size = NULL, epochs = 10, verbose = 1, callbacks = NULL, ...) Train a Keras model for a fixed number of epochs (iterations)

fit_generator() Fits the model on data yielded batch-by-batch by a generator

train_on_batch() **test_on_batch()** Single gradient update or model evaluation over one batch of samples

EVALUATE A MODEL

evaluate(object, x = NULL, y = NULL, batch_size = NULL) Evaluate a Keras model

evaluate_generator() Evaluates the model on a data generator

PREDICT

predict() Generate predictions from a Keras model

predict_proba() and **predict_classes()** Generates probability or class probability predictions for the input samples

predict_on_batch() Returns predictions for a single batch of samples

predict_generator() Generates predictions for the input samples from a data generator

OTHER MODEL OPERATIONS

summary() Print a summary of a Keras model

export_savedmodel() Export a saved model

get_layer() Retrieves a layer based on either its name (unique) or index

pop_layer() Remove the last layer in a model

save_model_hdf5(); **load_model_hdf5()** Save/Load models using HDF5 files

serialize_model(); **unserialize_model()** Serialize a model to an R object

clone_model() Clone a model instance

freeze_weights(); **unfreeze_weights()** Freeze and unfreeze weights

CORE LAYERS

layer_input() Input layer

layer_dense() Add a densely-connected NN layer to an output

layer_activation() Apply an activation function to an output

layer_dropout() Applies Dropout to the input

layer_reshape() Reshapes an output to a certain shape

layer_permute() Permute the dimensions of an input according to a given pattern

layer_repeat_vector() Repeats the input n times

layer_lambda(object, f) Wraps arbitrary expression as a layer

layer_activity_regularization() Layer that applies an update to the cost function based input activity

layer_masking() Masks a sequence by using a mask value to skip timesteps

layer_flatten() Flattens an input

TRAINING AN IMAGE RECOGNIZER ON MNIST DATA

```
# input layer: use MNIST images
mnist <- dataset_mnist()
x_train <- mnist$train$x; y_train <- mnist$train$y
x_test <- mnist$test$x; y_test <- mnist$test$y

# reshape and rescale
x_train <- array_reshape(x_train, c(nrow(x_train), 784))
x_test <- array_reshape(x_test, c(nrow(x_test), 784))
x_train <- x_train / 255; x_test <- x_test / 255

y_train <- to_categorical(y_train, 10)
y_test <- to_categorical(y_test, 10)

# defining the model and layers
model <- keras_model_sequential()
model %>%
  layer_dense(units = 256, activation = 'relu',
              input_shape = c(784)) %>%
  layer_dropout(rate = 0.4) %>%
  layer_dense(units = 128, activation = 'relu') %>%
  layer_dense(units = 10, activation = 'softmax')

# compile (define loss and optimizer)
model %>% compile(
  loss = 'categorical_crossentropy',
  optimizer = optimizer_rmsprop(),
  metrics = c('accuracy')
)

# train (fit)
model %>% fit(
  x_train, y_train,
  epochs = 30, batch_size = 128,
  validation_split = 0.2
)

model %>% evaluate(x_test, y_test)
model %>% predict_classes(x_test)
```
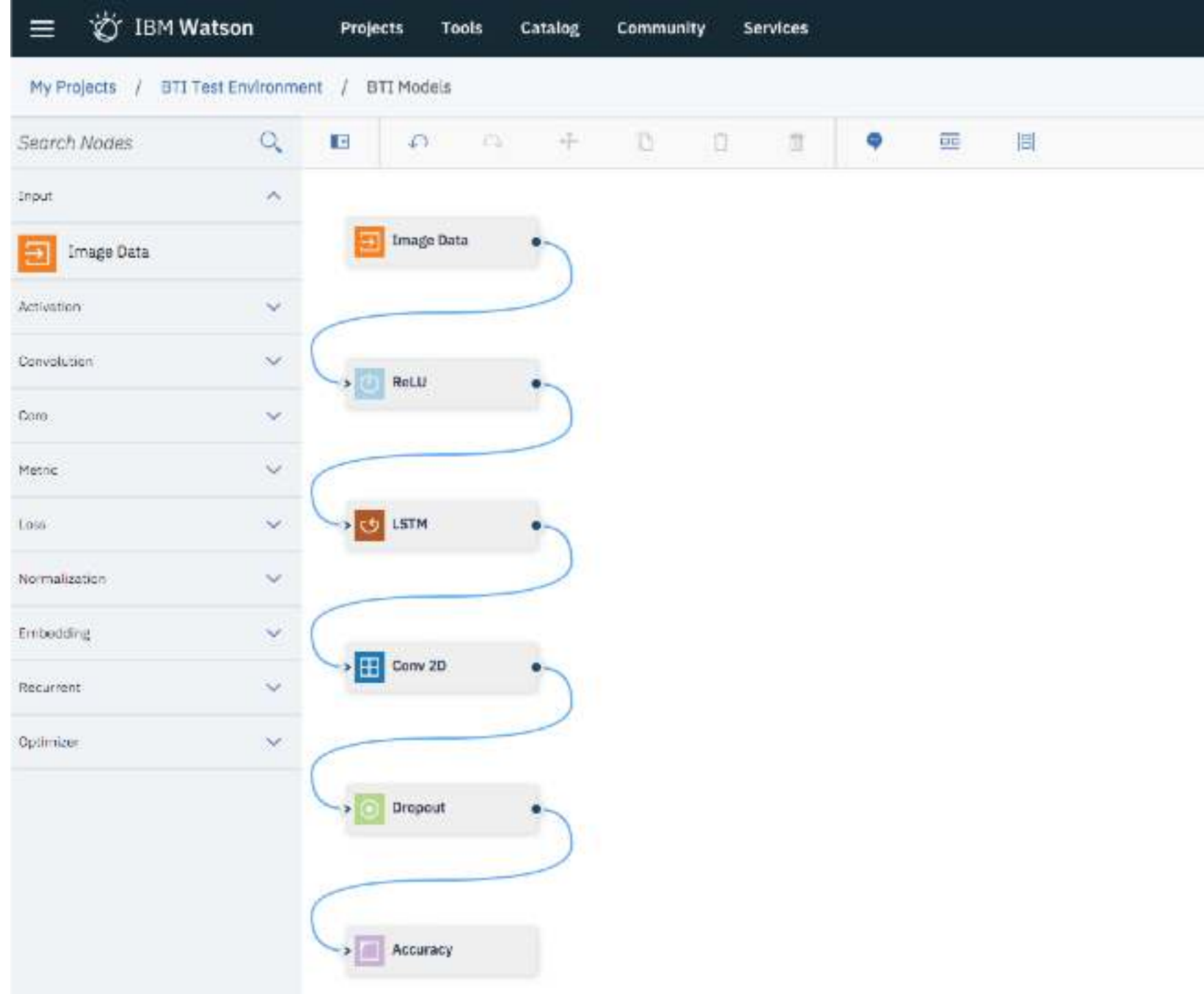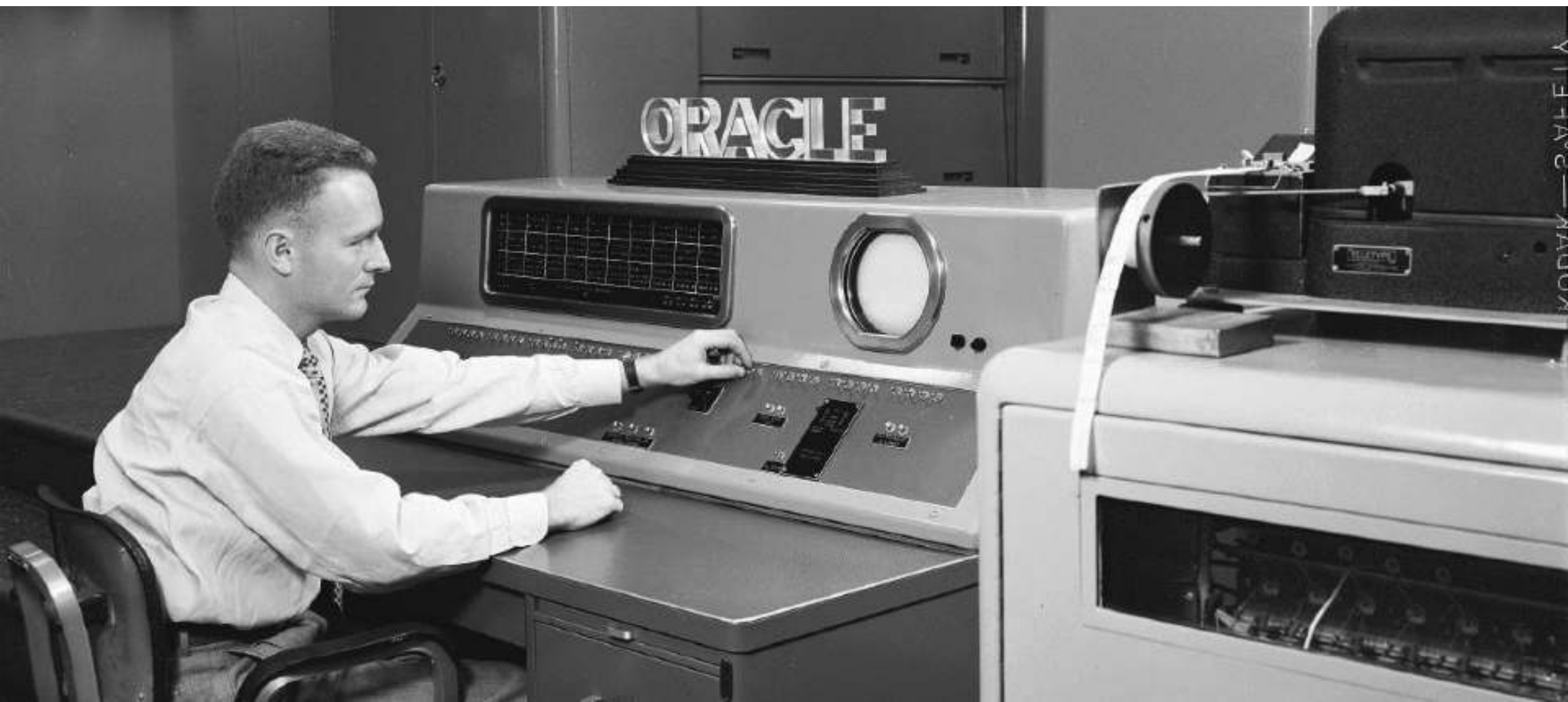
Let the machines do the heavy lifting

"Either you will manage the machines, or the machines will manage you." - @cspenn
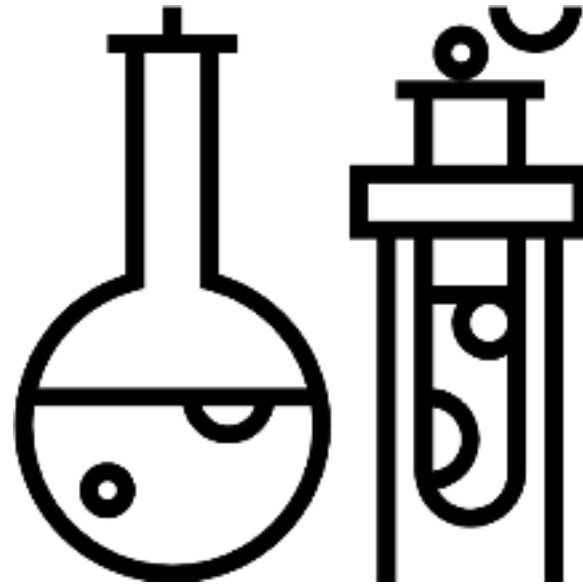
How to Prepare Your Company for AI

Who You'll Need

If Data Is **The New Oil**

Developers   **Data Scientists**   **Marketing Technologists**

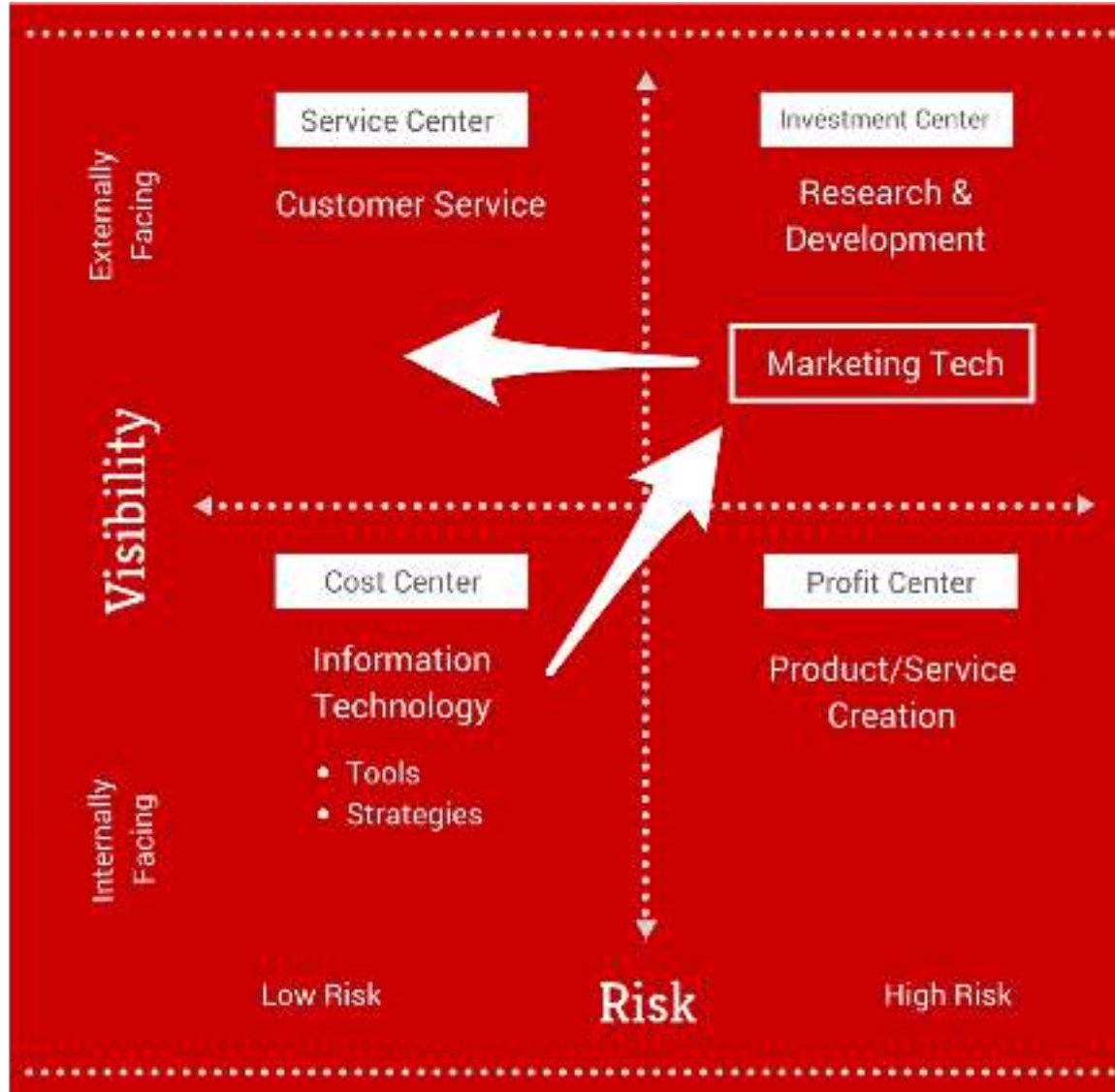# Developers

Data Scientists

Having learned parameter estimate $\widehat{\boldsymbol{\theta}}$, inference adoption probability is a relatively easier task. Given parameter estimate $\widehat{\boldsymbol{\theta}} = <\hat{p}_1, \hat{\lambda}_{I|1}, \hat{\lambda}_{E|1}, \hat{\lambda}_{S|1}, \hat{\lambda}_{H|1}, \hat{p}_0, \hat{\lambda}_{I|0}, \hat{\lambda}_{E|0}, \hat{\lambda}_{S|0}, \hat{\lambda}_{H|0}>$, by (12), we have

$$P(A_q = 1|I_q, E_q, S_q, H_q) = \frac{P(A_q = 1)P(I_q|A_q = 1)P(E_q|A_q = 1)P(S_q|A_q = 1)P(H_q|A_q = 1)}{\sum_{a=0,1} P(A_q = a)P(I_q|A_q = a)P(E_q|A_q = a)P(S_q|A_q = a)P(H_q|A_q = a)}$$

$$= \frac{\hat{p}_1 \hat{\lambda}_{I|1} \exp(-\hat{\lambda}_{I|1} I_q) \hat{\lambda}_{E|1} \exp(-\hat{\lambda}_{E|1} E_q) \hat{\lambda}_{S|1} \exp(-\hat{\lambda}_{S|1} S_q) \hat{\lambda}_{H|1} \exp(-\hat{\lambda}_{H|1} H_q)}{\sum_{a=0,1} \hat{p}_a \hat{\lambda}_{I|a} \exp(-\hat{\lambda}_{I|a} I_q) \hat{\lambda}_{E|a} \exp(-\hat{\lambda}_{E|a} E_q) \hat{\lambda}_{S|a} \exp(-\hat{\lambda}_{S|a} S_q) \hat{\lambda}_{H|a} \exp(-\hat{\lambda}_{H|a} H_q)}. \quad (42)$$

To compute adoption probability using (42), the only difficulty is the hidden variable H_q. However, given $\widehat{\boldsymbol{\theta}}$, probability density of H_q is known and we have

$$f(H_q|\widehat{\boldsymbol{\theta}}) = f(H_q|A_q = 1, \widehat{\boldsymbol{\theta}})P(A_q = 1|\widehat{\boldsymbol{\theta}}) + f(H_q|A_q = 0, \widehat{\boldsymbol{\theta}})P(A_q = 0|\widehat{\boldsymbol{\theta}}). \quad (43)$$

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