A DEVELOPERS GUIDE TO

MACHINE LEARNING

@TESSFERRANDEZ

[CLASSIFICATION]

```
IF PICTURE.CONTAINS(2 EYES && NOSE)
    RETURN CHIUAUA
ELSE IF PICTURE.CONTAINS(PAPERCUP)
    RETURN MUFFIN
ELSE
    RETURN I HAVE NO CLUE
```

from @teenybiscuit

Microsoft Azure

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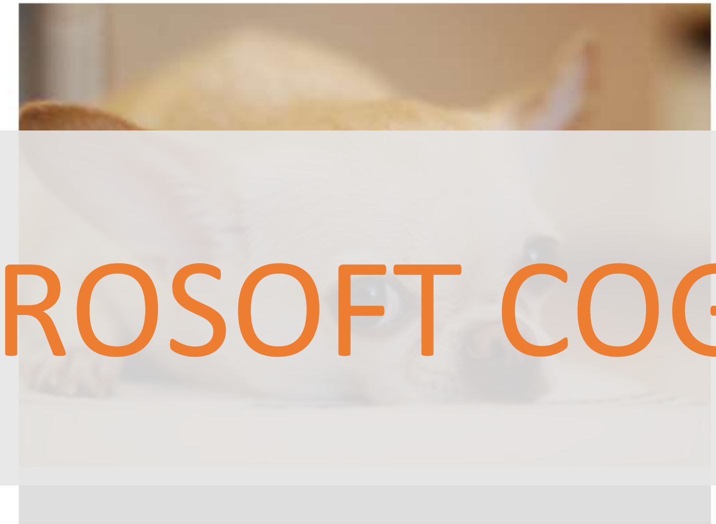
FREE ACCOUNT

[MICROSOFT COGNITIVE SERVICES]

Analyze an image

This feature returns information about visual content found in an image. Use tagging, descriptions, and domain-specific models to identify content and label it with confidence. Apply the adult/racy settings to enable automated restriction of adult content. Identify image types and color schemes in pictures.

See it in action



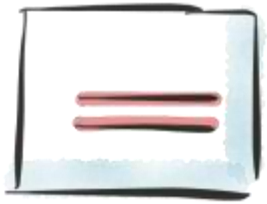
FEATURE NAME:	VALUE
Description	{ "tags": ["indoor", "dog", "small", "animal", "sitting", "looking", "brown", "top", "laying", "camera", "white", "cute", "front", "head", "lying", "table", "close", "face", "little", "eyes", "yellow", "bed", "mouth"], "captions": [{ "text": "a small brown and white dog looking at the camera", "confidence":
Tags	"confidence": 0.8870871 }, { "name": "mammal", "confidence": 0.7809002 }, { "name": "brown", "confidence": 0.7565178 }, { "name": "close", "confidence": 0.2025338 }, { "name": "staring", "confidence": 0.151472017 }]
Image format	"Jpeg"

Image URL | Submit | Browse

Want to build this?

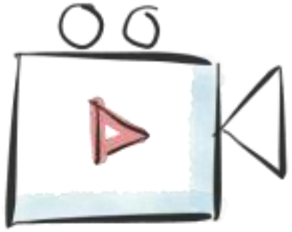
FACE RECOGNITION

STOCK PRICE



CREDIT CARD FRAUD

SENTIMENT ANALYSIS



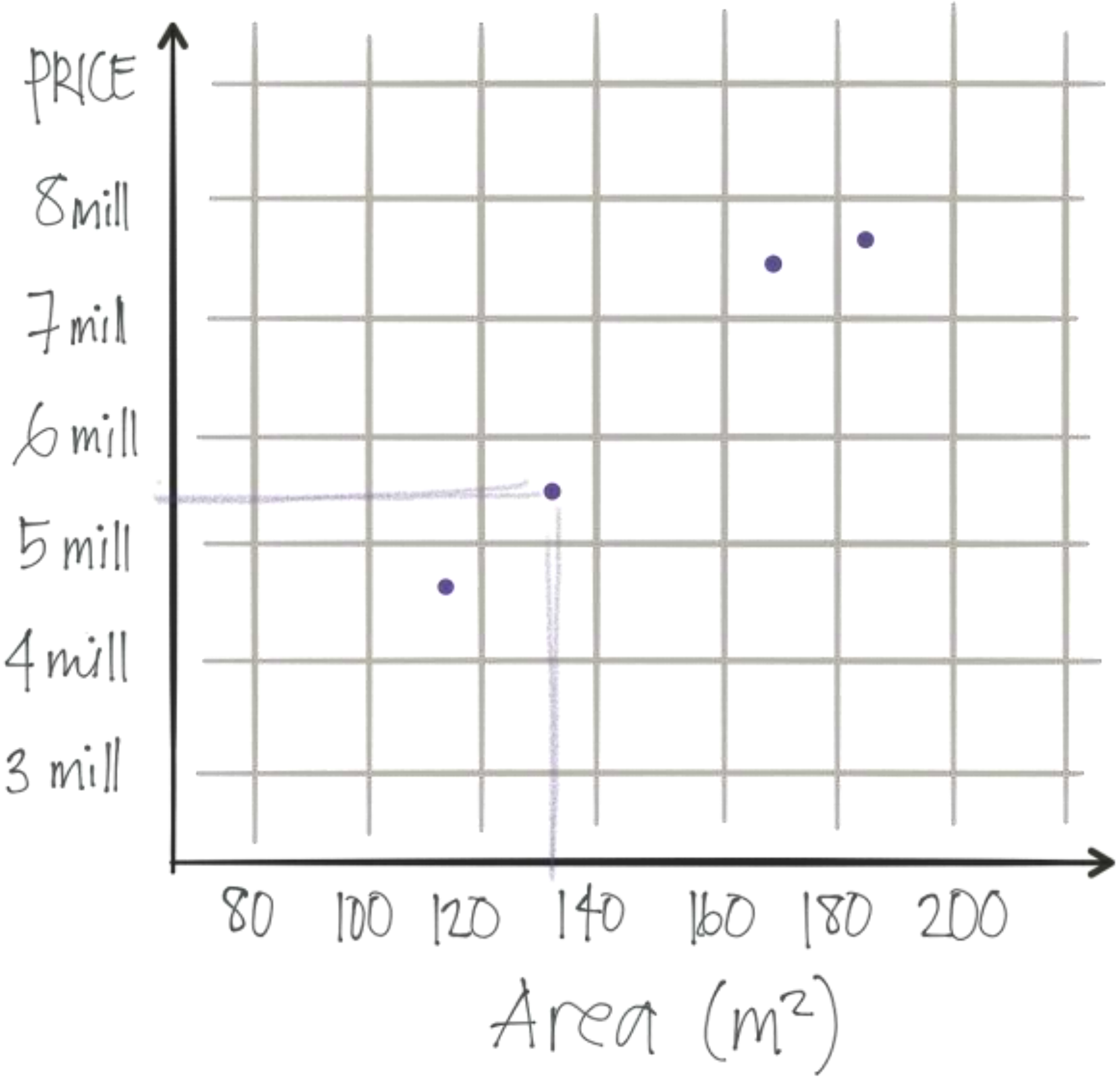
MOVIE RECOMMENDATION


1156

[REGRESSION]

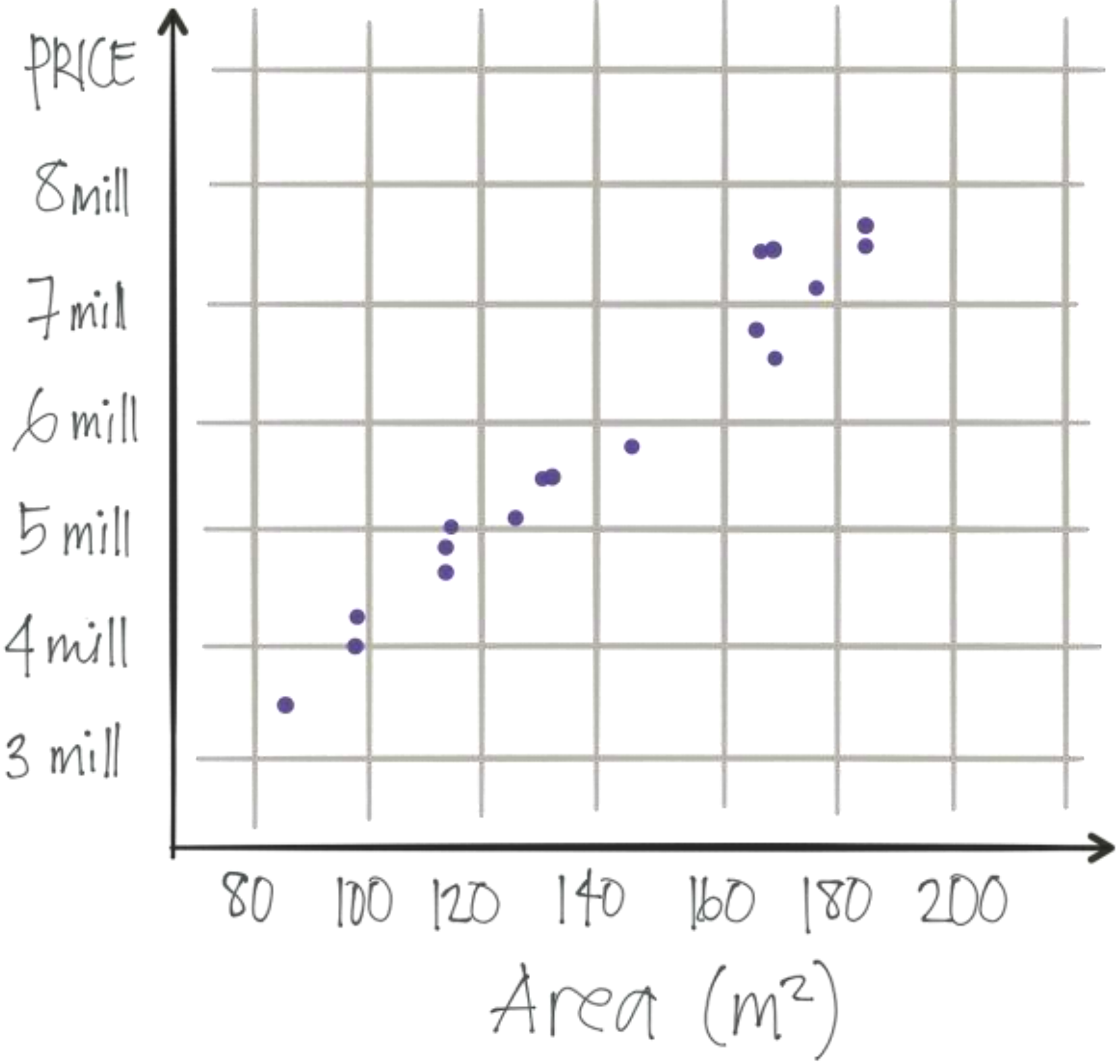
AREA m^2	PRICE Kkr
134	5 495
115	4 700
167	7 500
185	7775
84	3500
98	40000
115	4 850
185	7500
164	6900
145	5950
123	5010
128	5600
167	6750
115	5000
178	7200
97	4290

AREA m^2	PRICE Kkr
134	5 495
115	4 700
167	7 500
185	7775
84	3500
98	40000
115	4 850
185	7500
164	6900
145	5950
123	5010
128	5600
167	6750
115	5000
178	7200
97	4290



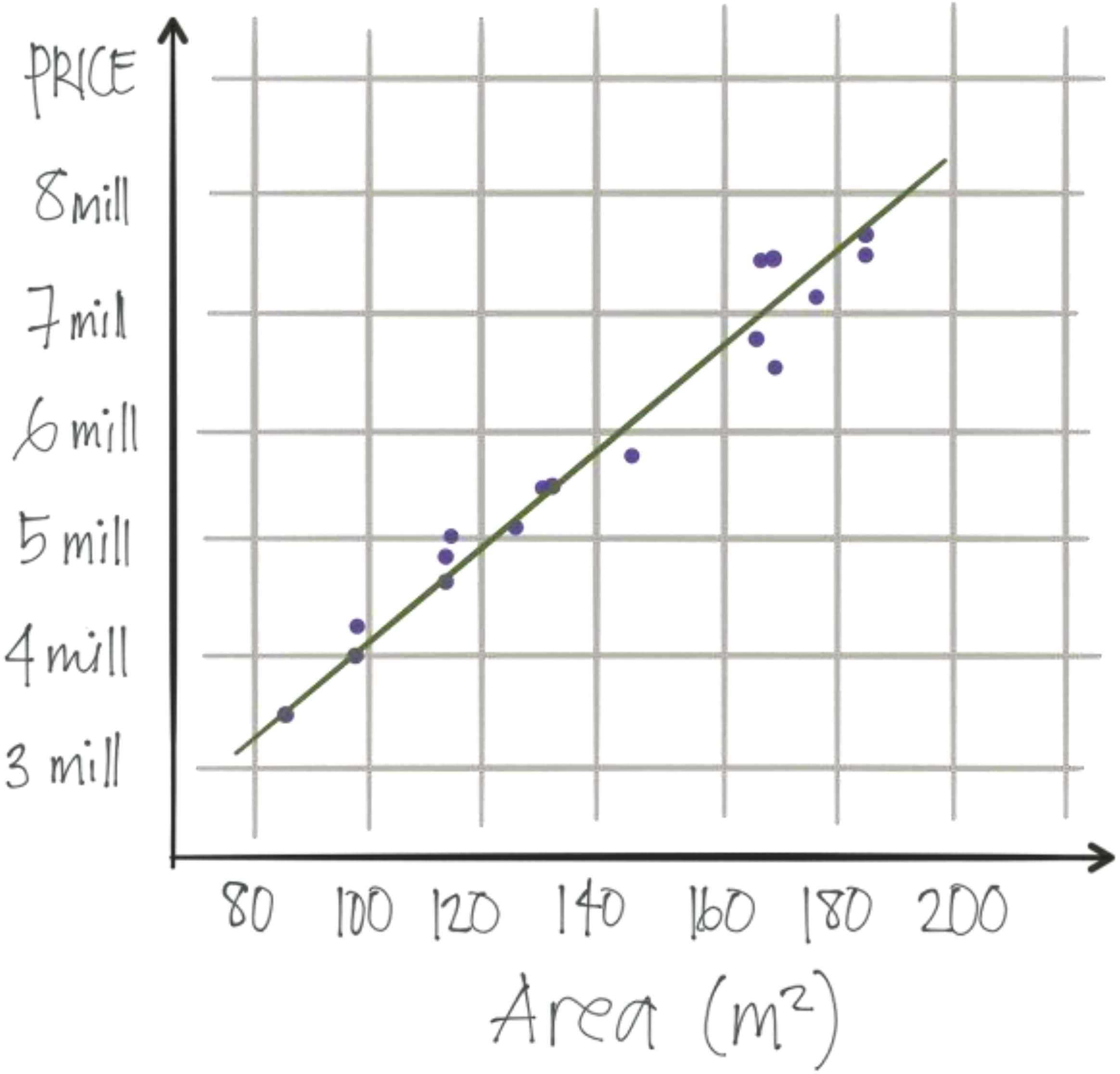
[SCATTER PLOT]

AREA m^2	PRICE Kkr
134	5 495
115	4 700
167	7 500
185	7775
84	3500
98	4000~~0~~
115	4 850
185	7500
164	6900
145	5950
123	5010
128	5600
167	6750
115	5000
178	7200
97	4290



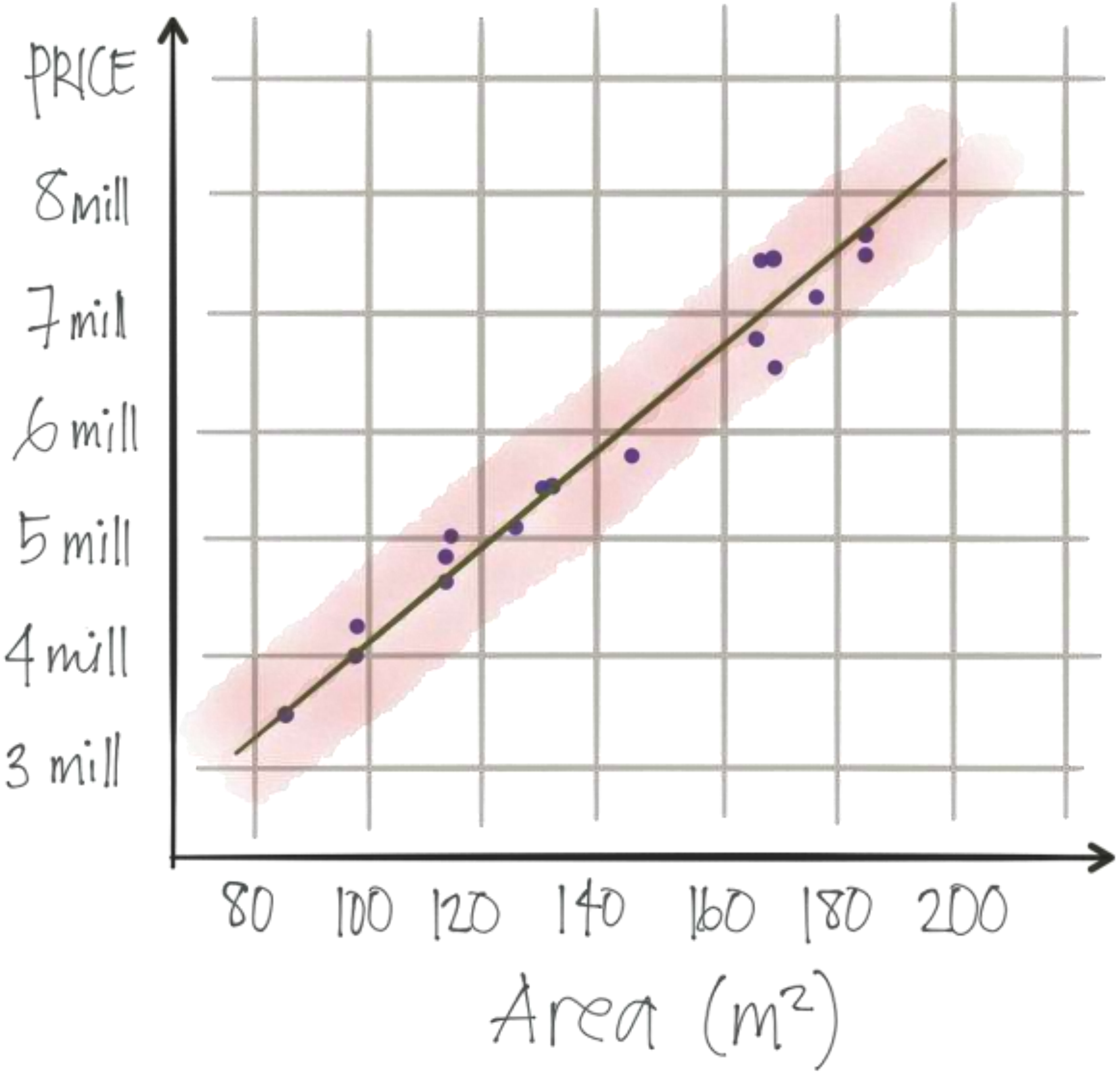
[LINEAR REGRESSION]

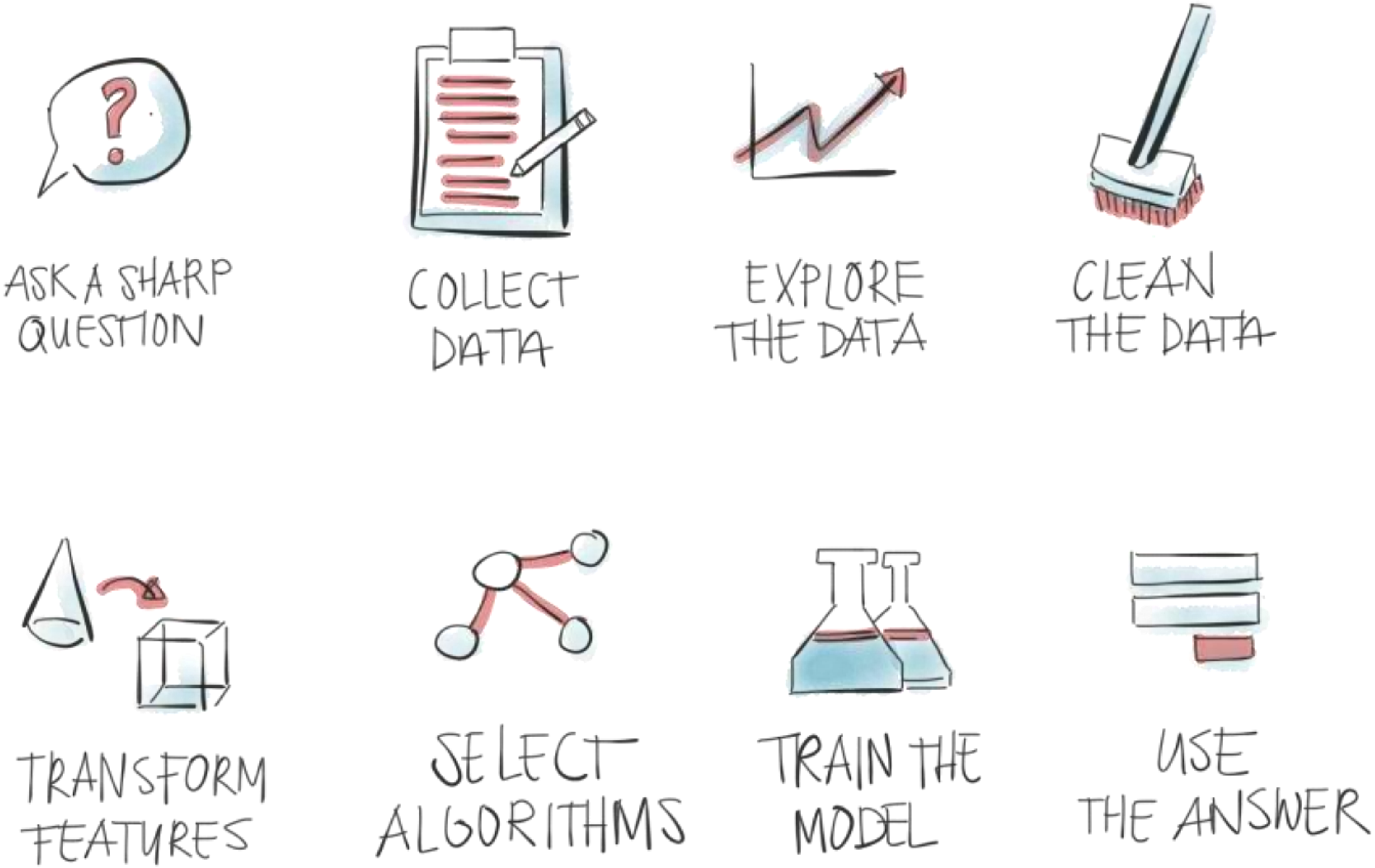
AREA m^2	PRICE Kkr
134	5 495
115	4 700
167	7 500
185	7775
84	3500
98	4000~~0~~
115	4 850
185	7500
164	6900
145	5950
123	5010
128	5600
167	6750
115	5000
178	7200
97	4290



[CONFIDENCE INTERVAL]

AREA m^2	PRICE Kkr
134	5 495
115	4 700
167	7 500
185	7775
84	3500
98	4000
115	4 850
185	7500
164	6900
145	5950
123	5010
128	5600
167	6750
115	5000
178	7200
97	4290




ASK A SHARP QUESTION
COLLECT DATA
EXPLORE THE DATA
CLEAN THE DATA
TRANSFORM FEATURES
SELECT ALGORITHMS
TRAIN THE MODEL
USE THE ANSWER

ASK A SHARP QUESTION

HOW MUCH? HOW MANY?

STOCK PRICE

TEMP°

PEOPLE WHO WILL BUY X

[REGRESSION]

IS IT THIS OR THAT?

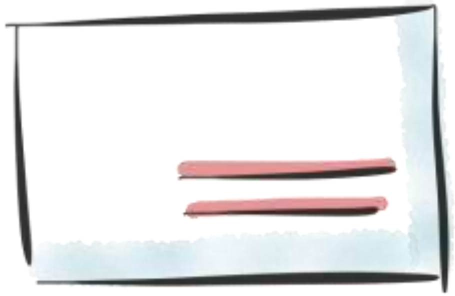
SPAM OR NO SPAM

SICK OR HEALTHY

NEWS ARTICLE TOPIC

[CLASSIFICATION]

IS THIS WEIRD?



CREDIT CARD FRAUD

REQUEST ANOMALIES

[ANOMALY DETECTION]

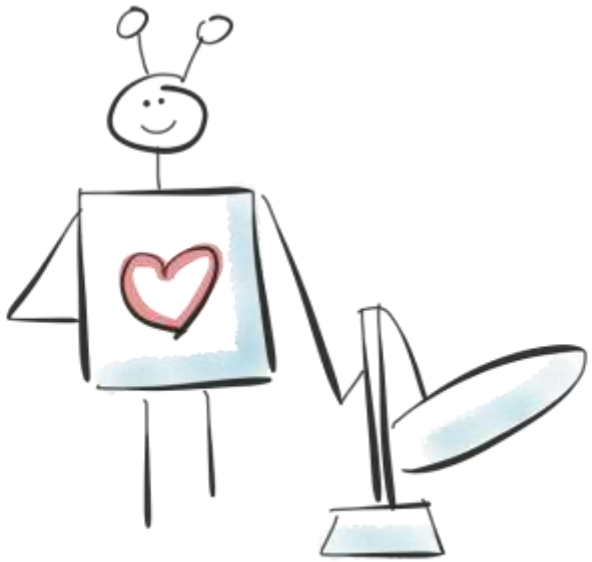
WHICH GROUPS?

WHICH VIEWERS LIKE SIMILAR MOVIES?

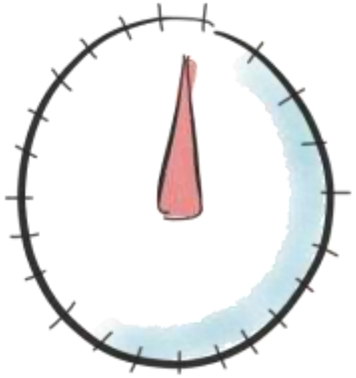
BREAK THESE PRODUCTS INTO 5 PRODUCT GROUPS

[CLUSTERING]

WHICH ACTION?



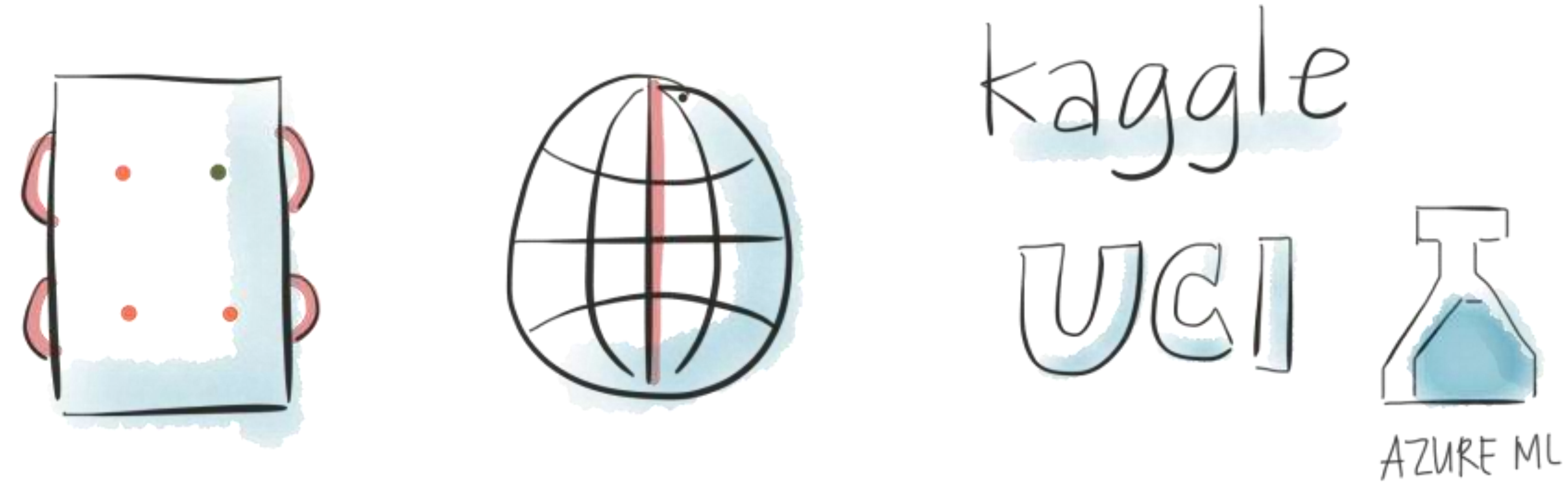
KEEP VACUUMING
OR CHARGE



RAISE OR LOWER
THE TEMPERATURE

[REINFORCMENT]

COLLECT
DATA

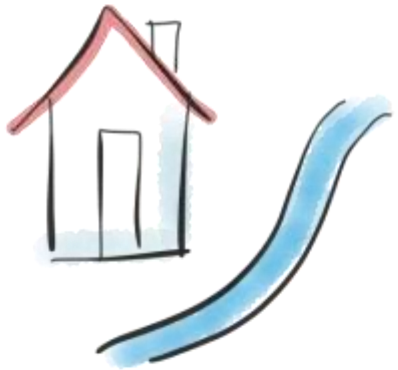

kaggle
UCI
AZURE ML



AREA (m^2)	TYPE	ZIP·CODE	PRICE (kkr)
134	HOUSE	90210	5 495
115	TOWNHOME	11436	4700
167	HOUSE	90210	7500
185	HOUSE	11436	7775
84	HOUSE	79021	3500
98	TOWNHOME	11436	4000

AREA (m^2)	TYPE	ZIP·CODE	PRICE (kkr)
134	HOUSE	90210	5 495
115	TOWNHOME	11436	4700
167	HOUSE	90210	7500
185	HOUSE	11436	7775
84	HOUSE	79021	3500
98	TOWNHOME	11436	4000

RELEVANT

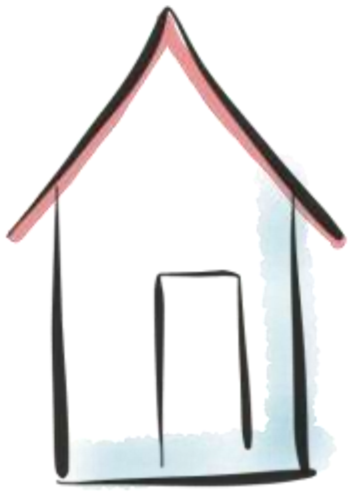


DISTANCE
TO WATER

INDEPENDENT

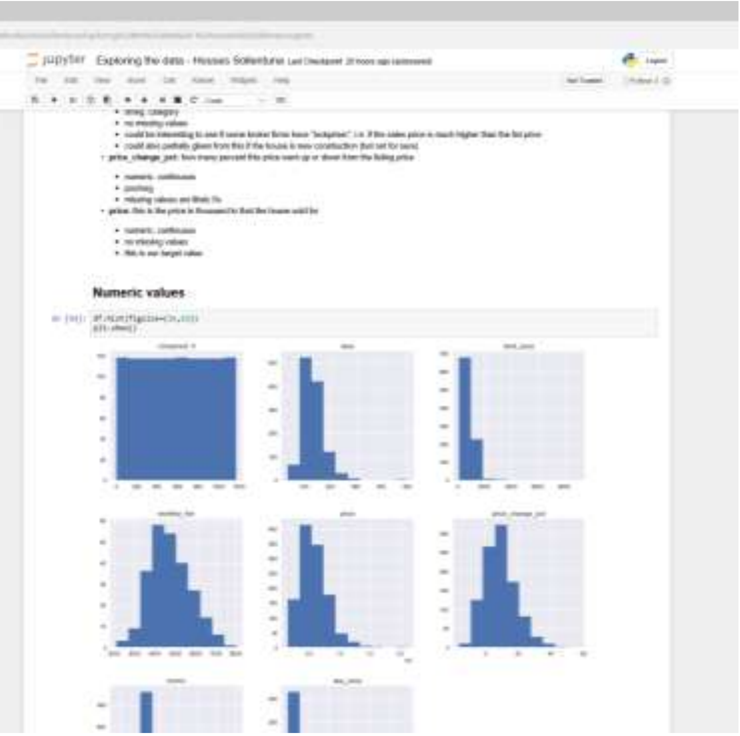
$120\ m^2$

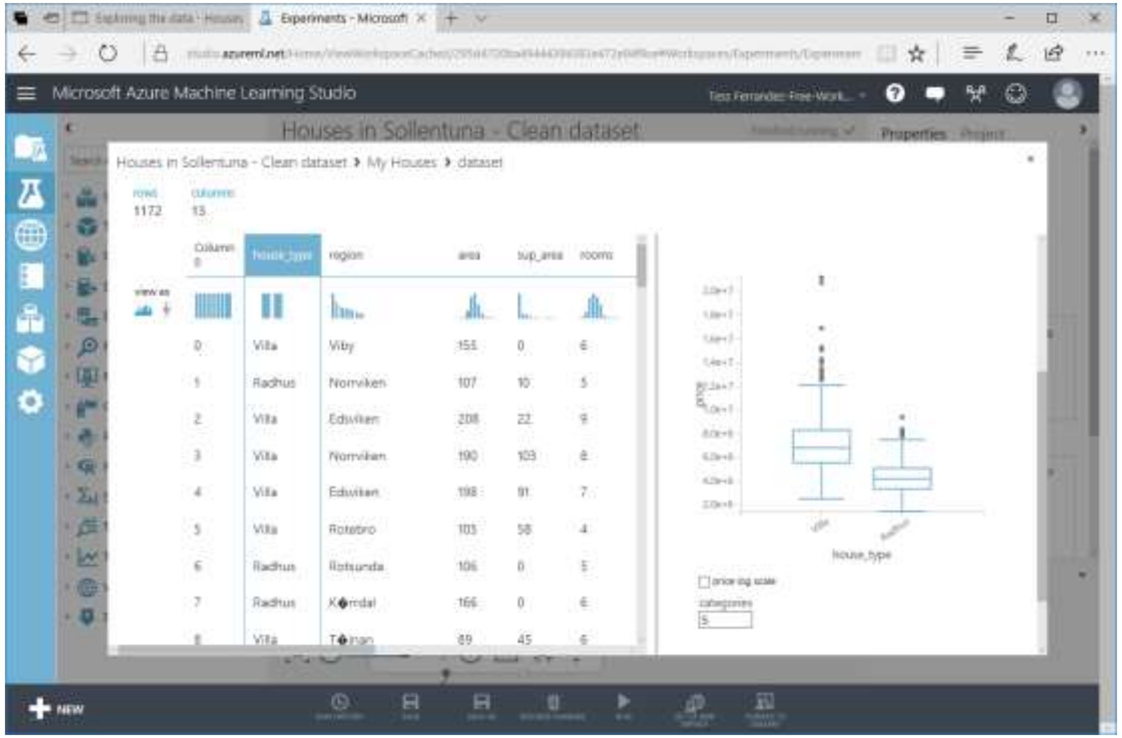
SIMPLE

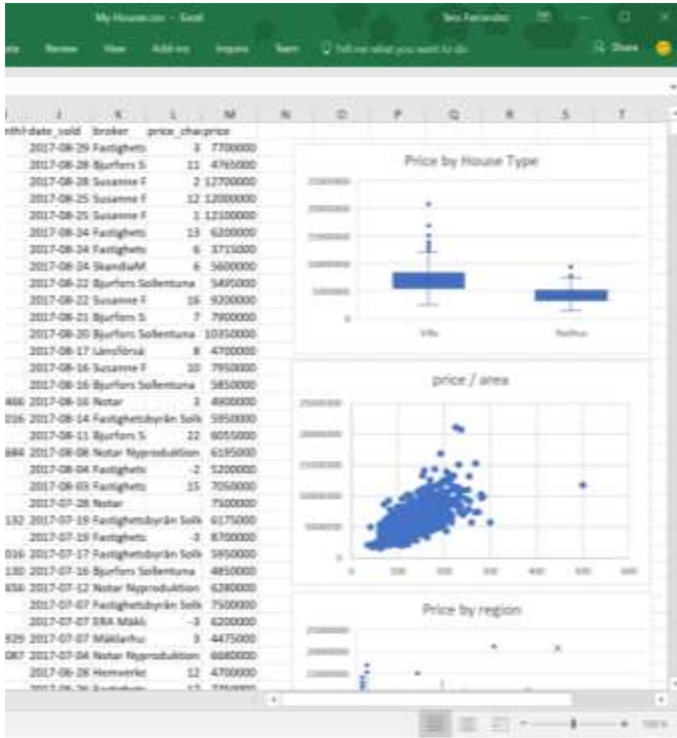


48° 51' 30.132" N
2° 17' 40.1316" E

EXPLORE
THE DATA


jupyter
Exploring the data - Houses Sollentuna
Numeric values

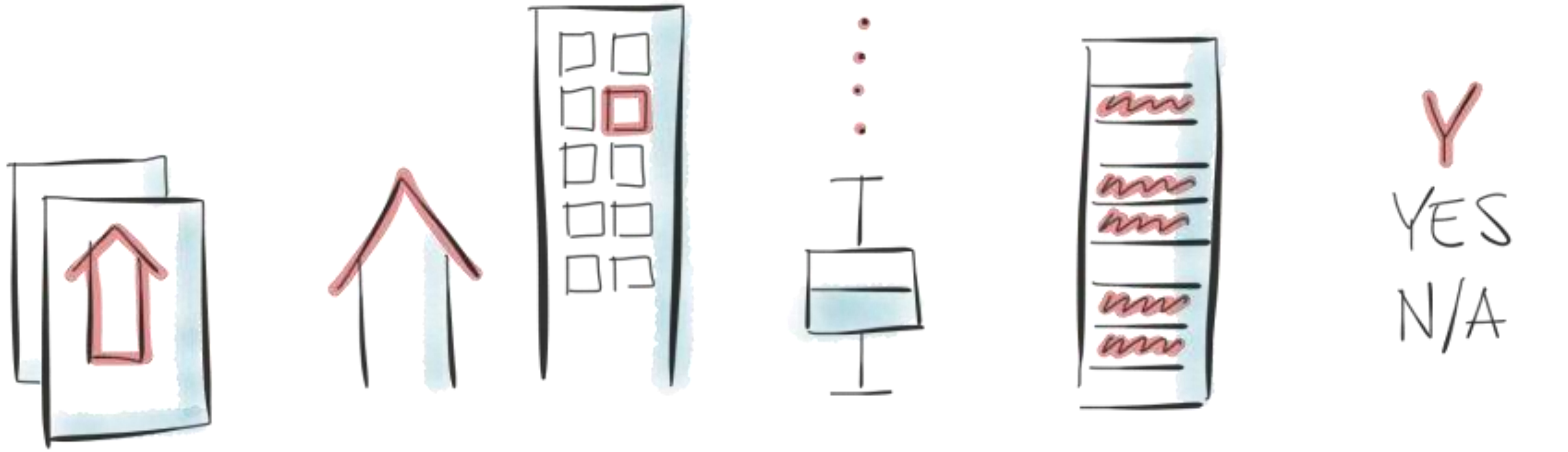

Microsoft Azure Machine Learning Studio
Houses in Sollentuna - Clean dataset
Houses in Sollentuna - Clean dataset › My Houses › dataset
rows
1172
columns
15
house_type
region
area
sup_area
rooms
NEW


Price by House Type
price / area
Price by region

	TYPE	EXPECT	MISSING	OUTLIERS	COMMENT
HOUSETYPE					
ADDRESS					
AREA					
SUP.AREA					
REGION					
MONTH FEE					
DATE SOLD					
BROKER					
PRICE CH%					
PRICE					

	TYPE	EXPECT	MISSING	OUTLIERS	COMMENT
HOUSETYPE	CAT				
ADDRESS	STR				
AREA	NUM				
SUP.AREA	NUM				
REGION	CAT				
MONTH FEE	NUM				
DATE SOLD	DATE				
BROKER	CAT				
PRICE CH%	NUM				
PRICE (T)	NUM				

	TYPE	EXPECT	MISSING	OUTLIERS	COMMENT
HOUSETYPE	CAT	HIGH			
ADDRESS	STR				
AREA	NUM	HIGH			
SUP.AREA	NUM	MED			
REGION	CAT	HIGH			
MONTH FEE	NUM	MED			
DATE SOLD	DATE	MED			
BROKER	CAT	?			
PRICE CH%	NUM				
PRICE (T)	NUM				



DUPLICATE OBSERVATIONS

IRRELEVANT OBSERVATIONS

OUTLIERS

MISSING DATA

STRUCTURAL ERRORS

[NUMERIC VS NUMERIC]

	TYPE	EXPECT	MISSING	OUTLIERS	COMMENT
HOUSETYPE	CAT	HIGH			
ADDRESS	STR				
AREA	NUM	HIGH			
SUP.AREA	NUM	MED			
REGION	CAT	HIGH			
MONTH FEE	NUM	MED			
DATE SOLD	DATE	MED			
BROKER	CAT	?			
PRICE CH%	NUM				
PRICE (T)	NUM				

	TYPE	EXPECT	MISSING	OUTLIERS	COMMENT
HOUSETYPE	CAT	HIGH	—		SEPARATE MODELS?
ADDRESS	STR		—		REMOVE
AREA	NUM	HIGH	REMOVE	>500	
SUP.AREA	NUM	MED	0		AREA+SUP=TOTAL
REGION	CAT	HIGH	UNKNOWN		COMBINE+CLEAN
MONTH FEE	NUM	MED	0		MISSING ⇒ CONDO
DATE SOLD	DATE	MED	—		⇒ YEAR, MONTH, RUNNING MONTH?
BROKER	CAT	?	UNKNOWN		CAUSE / EFFECT?
PRICE CH%	NUM				REM: NOT AVAIL UNTIL SOLD
PRICE (T)	NUM		—		TARGET

CLEAN
THE DATA

ID	First Name	Last Name	Birth Year	Height	Birthplace	Identity is secret	Can fly	Alignment	Wears cape
7435	Bruce	Wayne	1969*	6'2''	Gotham	Y	3	anti-villain	black
0958	Ororo	Munroe	--1979--	5'11''	Manhattan	NA	9	Good	long
9471	Diana	Trevor	1618	5'8''	Paradise Island	Y	Jet	truth	rarely
9483	Janet	Van Dyne	19.42	5'4''	Cresskill		tiny	Good	not really
0696	Peter	Parker	1111983	5'10''	Queens	Y	fall	right	never
5531	Harleen	Quinzell	1981	5'2''	Gotham	Y	-	evil	no
4734	Erik	Lehnsherr	1-9-3-2	6'0''	Hamburg	NA	lev.	mutants	Absolutely
7757	Natasha	Romanova	1983	5'7''	St. Petersburg	NA	jet	depends	No way
0323	Jean	Grey	"1977"	5'6''	Annandale		No	good	Mostly not
3990	Clark	Kent	"1954"	6'4''	Krypton	Y	12	truth	always
3057	Victor	Von Doom	"1943"	6'2''	Latveria	Missing	1	Bad	yes
0573	Stephen	Strange	1968	6'2''	Philadelphia		not	light	Y
7452	Thor	Odinson	2287 BC	6'6''	Norway		10	Good	Of course
1437	Selina	Kyle	1998	5'7''	Gotham	Y	NA	Neutral	It clashes
1883	Raven	Darkolme	..1911..	5'10''	unkown	Y	no	mostly bad	not really
5830	Kara	Zor-el	1961	5'7''	Krypton	Y	fast	G	Yes

ID	First Name	Last Name	Birth Year	Height	Birthplace	Identity is secret	Can fly	Alignment	Wears cape
7435	Bruce	Wayne	1969	6'2''	Gotham	Y	3	anti-villain	black
0958	Ororo	Munroe	1979	5'11''	Manhattan	NA	9	Good	long
9471	Diana	Trevor	1618	5'8''	Paradise Island	Y	Jet	truth	rarely
9483	Janet	Van Dyne	1942	5'4''	Cresskill		tiny	Good	not really
0696	Peter	Parker	1983	5'10''	Queens	Y	fall	right	never
5531	Harleen	Quinzell	1981	5'2''	Gotham	Y	-	evil	no
4734	Erik	Lehnsherr	1932	6'0''	Hamburg	NA	lev.	mutants	Absolutely
7757	Natasha	Romanova	1983	5'7''	St. Petersburg	NA	jet	depends	No way
0323	Jean	Grey	1977	5'6''	Annandale		No	good	Mostly not
3990	Clark	Kent	1954	6'4''	Krypton	Y	12	truth	always
3057	Victor	Von Doom	1943	6'2''	Latveria	Missing	1	Bad	yes
0573	Stephen	Strange	1968	6'2''	Philadelphia		not	light	Y
7452	Thor	Odinson	-2287	6'6''	Norway		10	Good	Of course
1437	Selina	Kyle	1998	5'7''	Gotham	Y	NA	Neutral	It clashes
1883	Raven	Darkolme	1911	5'10''	unkown	Y	no	mostly bad	not really
5830	Kara	Zor-el	1961	5'7''	Krypton	Y	fast	G	Yes

ID	First Name	Last Name	Birth Year	Height	Birthplace	Identity is secret	Can fly	Alignment	Wears cape
7435	Bruce	Wayne	1969	74	Gotham	Y	3	anti-villain	black
0958	Ororo	Munroe	1979	71	Manhattan	NA	9	Good	long
9471	Diana	Trevor	1618	68	Paradise Island	Y	Jet	truth	rarely
9483	Janet	Van Dyne	1942	64	Cresskill		tiny	Good	not really
0696	Peter	Parker	1983	70	Queens	Y	fall	right	never
5531	Harleen	Quinzell	1981	62	Gotham	Y	-	evil	no
4734	Erik	Lehnsherr	1932	72	Hamburg	NA	lev.	mutants	Absolutely
7757	Natasha	Romanova	1983	67	St. Petersburg	NA	jet	depends	No way
0323	Jean	Grey	1977	66	Annandale		No	good	Mostly not
3990	Clark	Kent	1954	76	Krypton	Y	12	truth	always
3057	Victor	Von Doom	1943	74	Latveria	Missing	1	Bad	yes
0573	Stephen	Strange	1968	74	Philadelphia		not	light	Y
7452	Thor	Odinson	-2287	78	Norway		10	Good	Of course
1437	Selina	Kyle	1998	67	Gotham	Y	NA	Neutral	It clashes
1883	Raven	Darkolme	1911	70	unkown	Y	no	mostly bad	not really
5830	Kara	Zor-el	1961	67	Krypton	Y	fast	G	Yes

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0958	Ororo	Munroe	1979	71	Manhattan	N	9	Good	long
9471	Diana	Trevor	1618	68	Paradise Island	Y	Jet	truth	rarely
9483	Janet	Van Dyne	1942	64	Cresskill	N	tiny	Good	not really
0696	Peter	Parker	1983	70	Queens	Y	fall	right	never
5531	Harleen	Quinzell	1981	62	Gotham	Y	-	evil	no
4734	Erik	Lehnsherr	1932	72	Hamburg	N	lev.	mutants	Absolutely
7757	Natasha	Romanova	1983	67	St. Petersburg	N	jet	depends	No way
0323	Jean	Grey	1977	66	Annandale	N	No	good	Mostly not
3990	Clark	Kent	1954	76	Krypton	Y	12	truth	always
3057	Victor	Von Doom	1943	74	Latveria	N	1	Bad	yes
0573	Stephen	Strange	1968	74	Philadelphia	N	not	light	Y
7452	Thor	Odinson	-2287	78	Norway	N	10	Good	Of course
1437	Selina	Kyle	1998	67	Gotham	Y	NA	Neutral	It clashes
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5830	Kara	Zor-el	1961	67	Krypton	Y	fast	G	Yes

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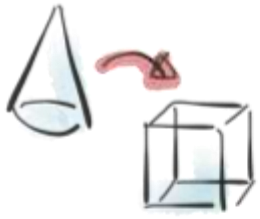
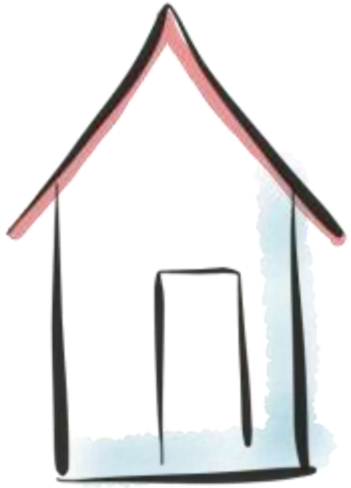
0958	Ororo	Munroe	1979	71	Manhattan	N	Y	Good	long
9471	Diana	Trevor	1618	68	Paradise Island	Y	N	truth	rarely
9483	Janet	Van Dyne	1942	64	Cresskill	N	N	Good	not really
0696	Peter	Parker	1983	70	Queens	Y	N	right	never
5531	Harleen	Quinzell	1981	62	Gotham	Y	N	evil	no
4734	Erik	Lehnsherr	1932	72	Hamburg	N	N	mutants	Absolutely
7757	Natasha	Romanova	1983	67	St. Petersburg	N	N	depends	No way
0323	Jean	Grey	1977	66	Annandale	N	N	good	Mostly not
3990	Clark	Kent	1954	76	Krypton	Y	Y	truth	always
3057	Victor	Von Doom	1943	74	Latveria	N	N	Bad	yes
0573	Stephen	Strange	1968	74	Philadelphia	N	N	light	Y
7452	Thor	Odinson	-2287	78	Norway	N	Y	Good	Of course
1437	Selina	Kyle	1998	67	Gotham	Y	N	Neutral	It clashes
1883	Raven	Darkolme	1911	70	unkown	Y	N	mostly bad	not really
5830	Kara	Zor-el	1961	67	Krypton	Y	Y	G	Yes

ID	First Name	Last Name	Birth Year	Height	Birthplace	Identity is secret	Can fly	Alignment	Wears cape
7435	Bruce	Wayne	1969	74	Gotham	Y	N	Good	black
0958	Ororo	Munroe	1979	71	Manhattan	N	Y	Good	long
9471	Diana	Trevor	1618	68	Paradise Island	Y	N	Good	rarely
9483	Janet	Van Dyne	1942	64	Cresskill	N	N	Good	not really
0696	Peter	Parker	1983	70	Queens	Y	N	Good	never
5531	Harleen	Quinzell	1981	62	Gotham	Y	N	Bad	no
4734	Erik	Lehnsherr	1932	72	Hamburg	N	N	Bad	Absolutely
7757	Natasha	Romanova	1983	67	St. Petersburg	N	N	Good	No way
0323	Jean	Grey	1977	66	Annandale	N	N	Good	Mostly not
3990	Clark	Kent	1954	76	Krypton	Y	Y	Good	always
3057	Victor	Von Doom	1943	74	Latveria	N	N	Bad	yes
0573	Stephen	Strange	1968	74	Philadelphia	N	N	Good	Y
7452	Thor	Odinson	-2287	78	Norway	N	Y	Good	Of course
1437	Selina	Kyle	1998	67	Gotham	Y	N	Neutral	It clashes
1883	Raven	Darkolme	1911	70	unkown	Y	N	Bad	not really
5830	Kara	Zor-el	1961	67	Krypton	Y	Y	Good	Yes

ID	First Name	Last Name	Birth Year	Height	Birthplace	Identity is secret	Can fly	Alignment	Wears cape
7435	Bruce	Wayne	1969	74	Gotham	Y	N	Good	Y
0958	Ororo	Munroe	1979	71	Manhattan	N	Y	Good	Y
9471	Diana	Trevor	1618	68	Paradise Island	Y	N	Good	N
9483	Janet	Van Dyne	1942	64	Cresskill	N	N	Good	N
0696	Peter	Parker	1983	70	Queens	Y	N	Good	N
5531	Harleen	Quinzell	1981	62	Gotham	Y	N	Bad	N
4734	Erik	Lehnsherr	1932	72	Hamburg	N	N	Bad	Y
7757	Natasha	Romanova	1983	67	St. Petersburg	N	N	Good	N
0323	Jean	Grey	1977	66	Annandale	N	N	Good	N
3990	Clark	Kent	1954	76	Krypton	Y	Y	Good	Y
3057	Victor	Von Doom	1943	74	Latveria	N	N	Bad	Y
0573	Stephen	Strange	1968	74	Philadelphia	N	N	Good	Y
7452	Thor	Odinson	-2287	78	Norway	N	Y	Good	Y
1437	Selina	Kyle	1998	67	Gotham	Y	N	Neutral	N
1883	Raven	Darkolme	1911	70	unkown	Y	N	Bad	N
5830	Kara	Zor-el	1961	67	Krypton	Y	Y	Good	Y



TRANSFORM
FEATURES



48° 51' 30.132" N
2° 17' 40.1316" E


JAN
17
JUN
21

SELECT
ALGORITHMS

[LINEAR REGRESSION]

AREA m^2	PRICE Kkr
134	5 495
115	4 700
167	7 500
185	7775
84	3500
98	4000~~0~~
115	4 850
185	7500
164	6900
145	5950
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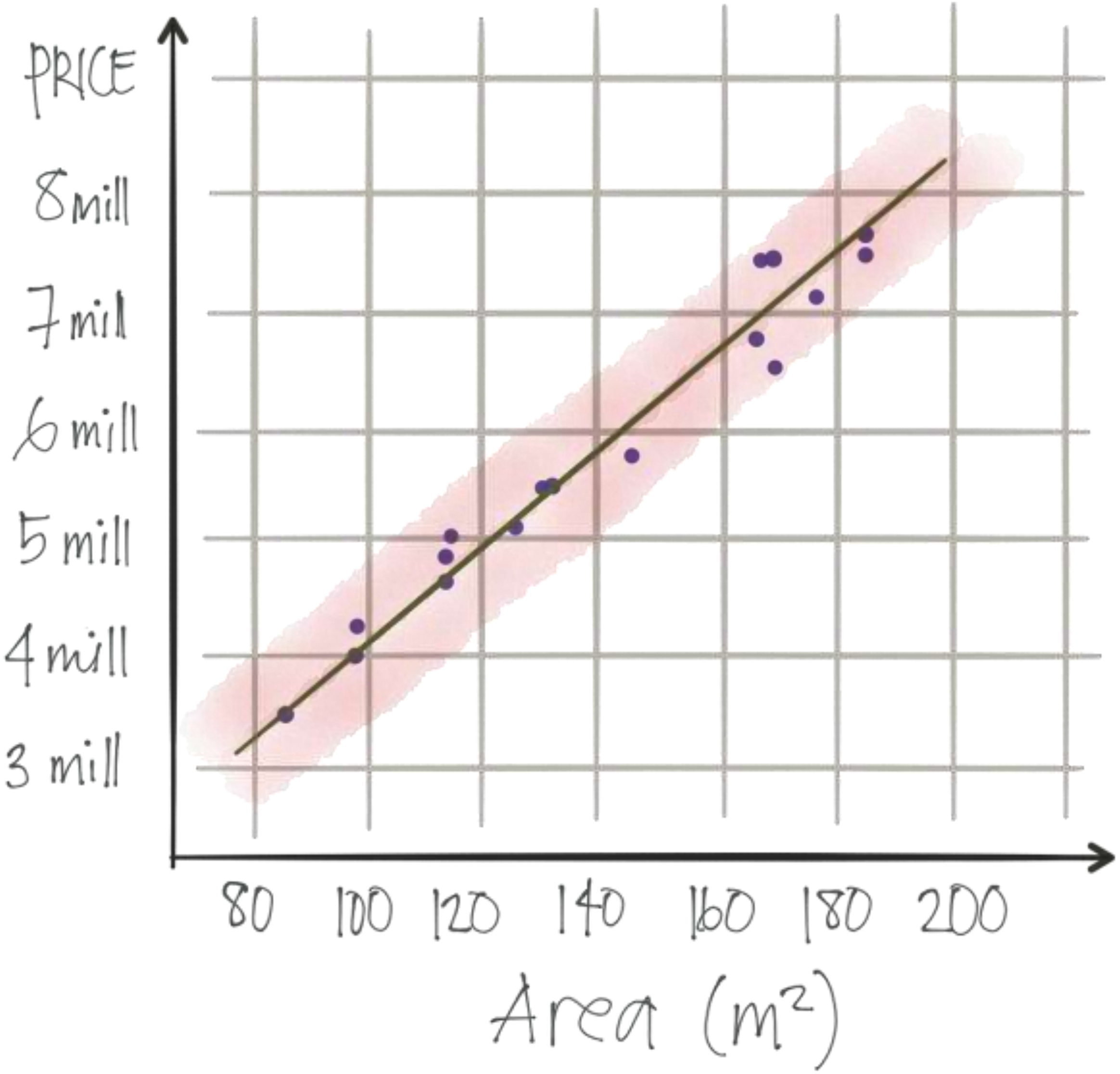


ANYONE FOR TENNIS?

OUTLOOK	TEMP	HUMIDITY	WINDY	PLAY
SUNNY	HOT	HIGH	FALSE	NO
SUNNY	HOT	HIGH	TRUE	NO
OVERCAST	HOT	HIGH	FALSE	YES
RAINY	MILD	HIGH	FALSE	YES
RAINY	COOL	NORMAL	FALSE	YES
RAINY	COOL	NORMAL	TRUE	NO
OVERCAST	COOL	NORMAL	TRUE	YES
SUNNY	MILD	HIGH	FALSE	NO
SUNNY	COOL	NORMAL	FALSE	YES
RAINY	MILD	NORMAL	FALSE	YES
SUNNY	MILD	NORMAL	TRUE	YES
OVERCAST	MILD	HIGH	TRUE	YES
OVERCAST	HOT	NORMAL	FALSE	YES
RAINY	MILD	HIGH	TRUE	NO

[DECISION TREE]

ANYONE FOR TENNIS?

OUTLOOK	TEMP	HUMIDITY	WINDY	PLAY
SUNNY	HOT	HIGH	FALSE	NO
SUNNY	HOT	HIGH	TRUE	NO
OVERCAST	HOT	HIGH	FALSE	YES
RAINY	MILD	HIGH	FALSE	YES
RAINY	COOL	NORMAL	FALSE	YES
RAINY	COOL	NORMAL	TRUE	NO
OVERCAST	COOL	NORMAL	TRUE	YES
SUNNY	MILD	HIGH	FALSE	NO
SUNNY	COOL	NORMAL	FALSE	YES
RAINY	MILD	NORMAL	FALSE	YES
SUNNY	MILD	NORMAL	TRUE	YES
OVERCAST	MILD	HIGH	TRUE	YES
OVERCAST	HOT	NORMAL	FALSE	YES
RAINY	MILD	HIGH	TRUE	NO

[DECISION TREE]

ANYONE FOR TENNIS?

OUTLOOK	TEMP	HUMIDITY	WINDY	PLAY
SUNNY	HOT	HIGH	FALSE	NO
SUNNY	HOT	HIGH	TRUE	NO
OVERCAST	HOT	HIGH	FALSE	YES
RAINY	MILD	HIGH	FALSE	YES
RAINY	COOL	NORMAL	FALSE	YES
RAINY	COOL	NORMAL	TRUE	NO
OVERCAST	COOL	NORMAL	TRUE	YES
SUNNY	MILD	HIGH	FALSE	NO
SUNNY	COOL	NORMAL	FALSE	YES
RAINY	MILD	NORMAL	FALSE	YES
SUNNY	MILD	NORMAL	TRUE	YES
OVERCAST	MILD	HIGH	TRUE	YES
OVERCAST	HOT	NORMAL	FALSE	YES
RAINY	MILD	HIGH	TRUE	NO

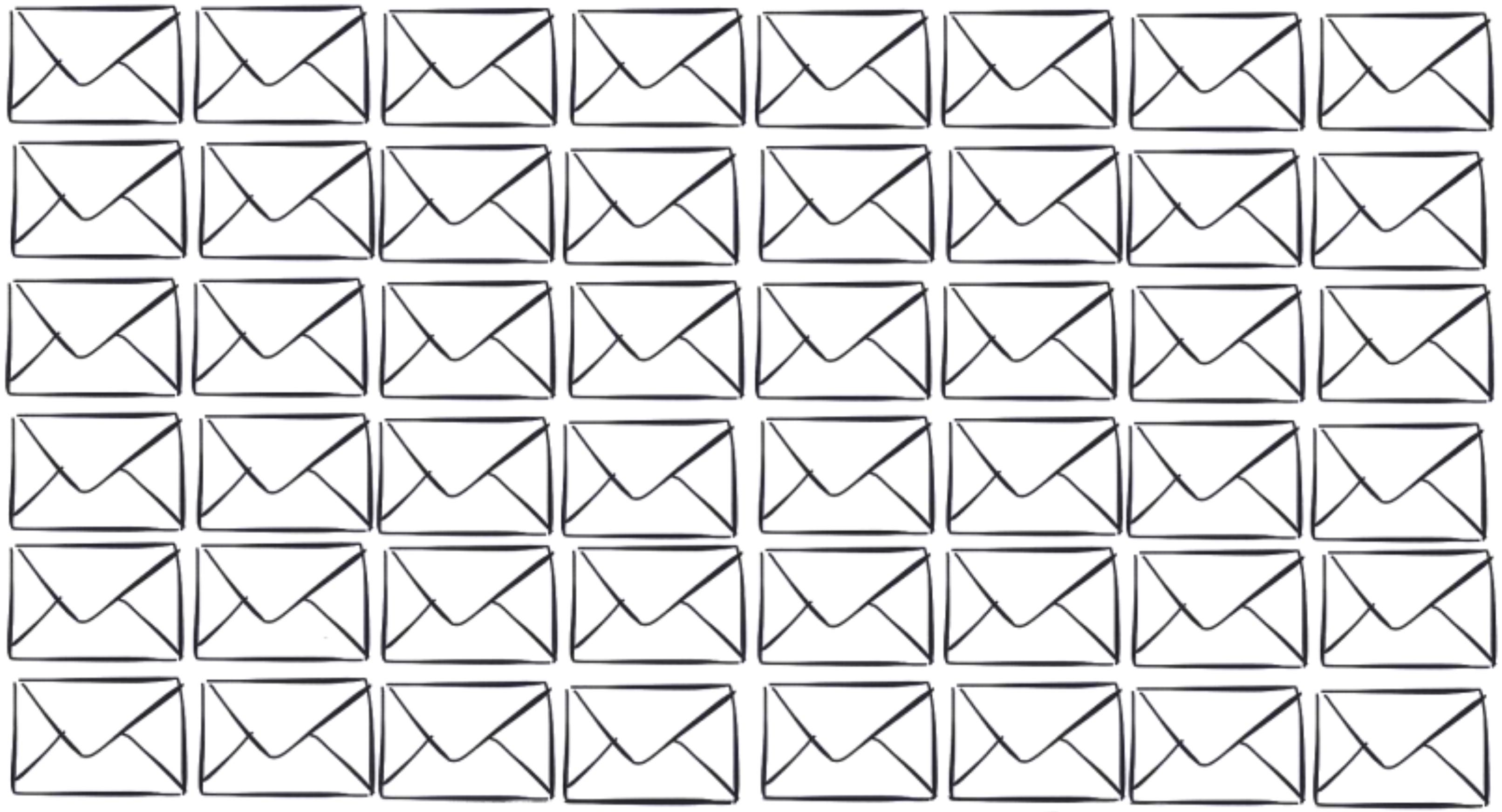
[DECISION TREE]

ANYONE FOR TENNIS?

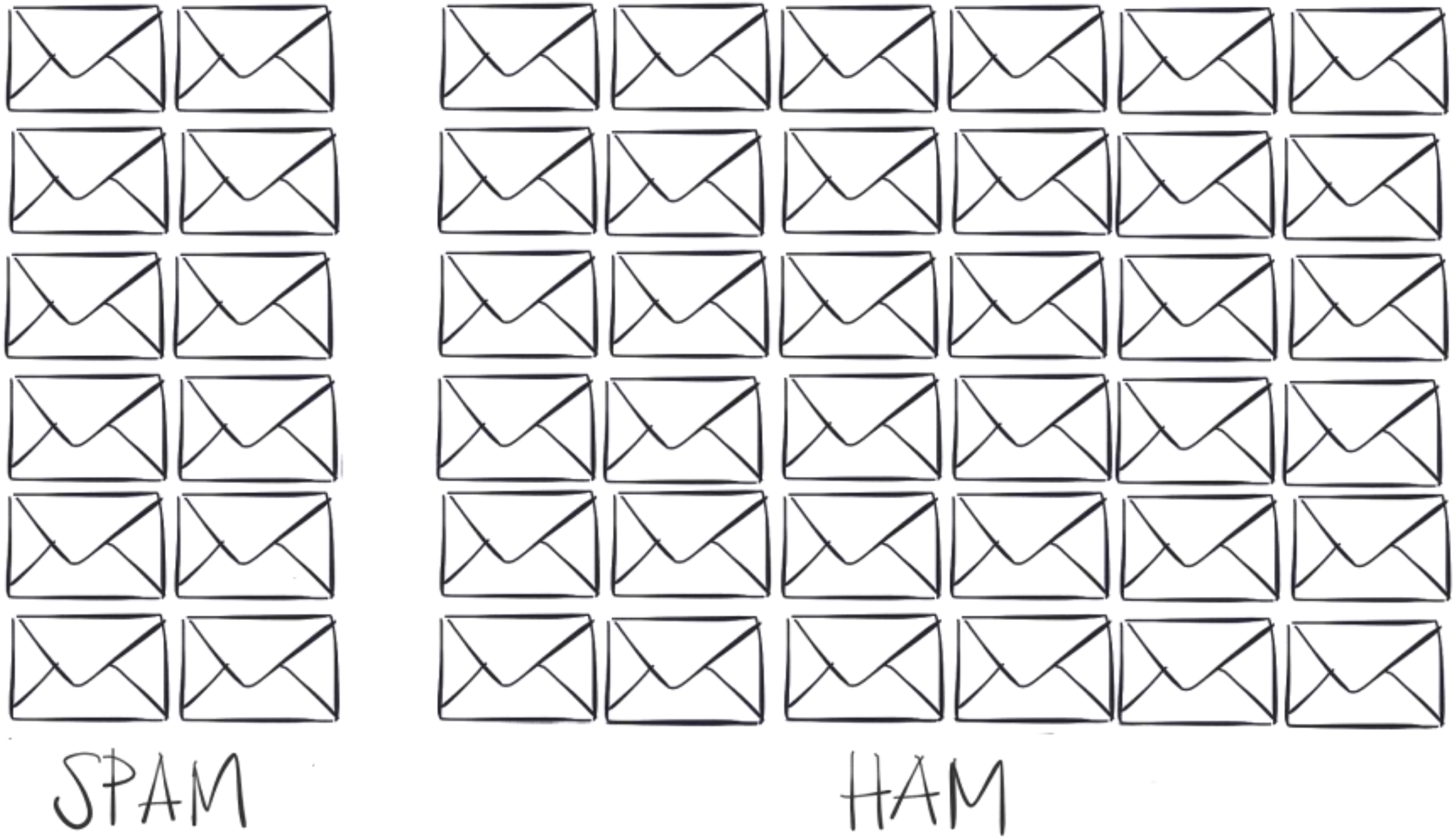
OUTLOOK	TEMP	HUMIDITY	WINDY	PLAY
SUNNY	HOT	HIGH	FALSE	NO
SUNNY	HOT	HIGH	TRUE	NO
OVERCAST	HOT	HIGH	FALSE	YES
RAINY	MILD	HIGH	FALSE	YES
RAINY	COOL	NORMAL	FALSE	YES
RAINY	COOL	NORMAL	TRUE	NO
OVERCAST	COOL	NORMAL	TRUE	YES
SUNNY	MILD	HIGH	FALSE	NO
SUNNY	COOL	NORMAL	FALSE	YES
RAINY	MILD	NORMAL	FALSE	YES
SUNNY	MILD	NORMAL	TRUE	YES
OVERCAST	MILD	HIGH	TRUE	YES
OVERCAST	HOT	NORMAL	FALSE	YES
RAINY	MILD	HIGH	TRUE	NO

[DECISION TREE]

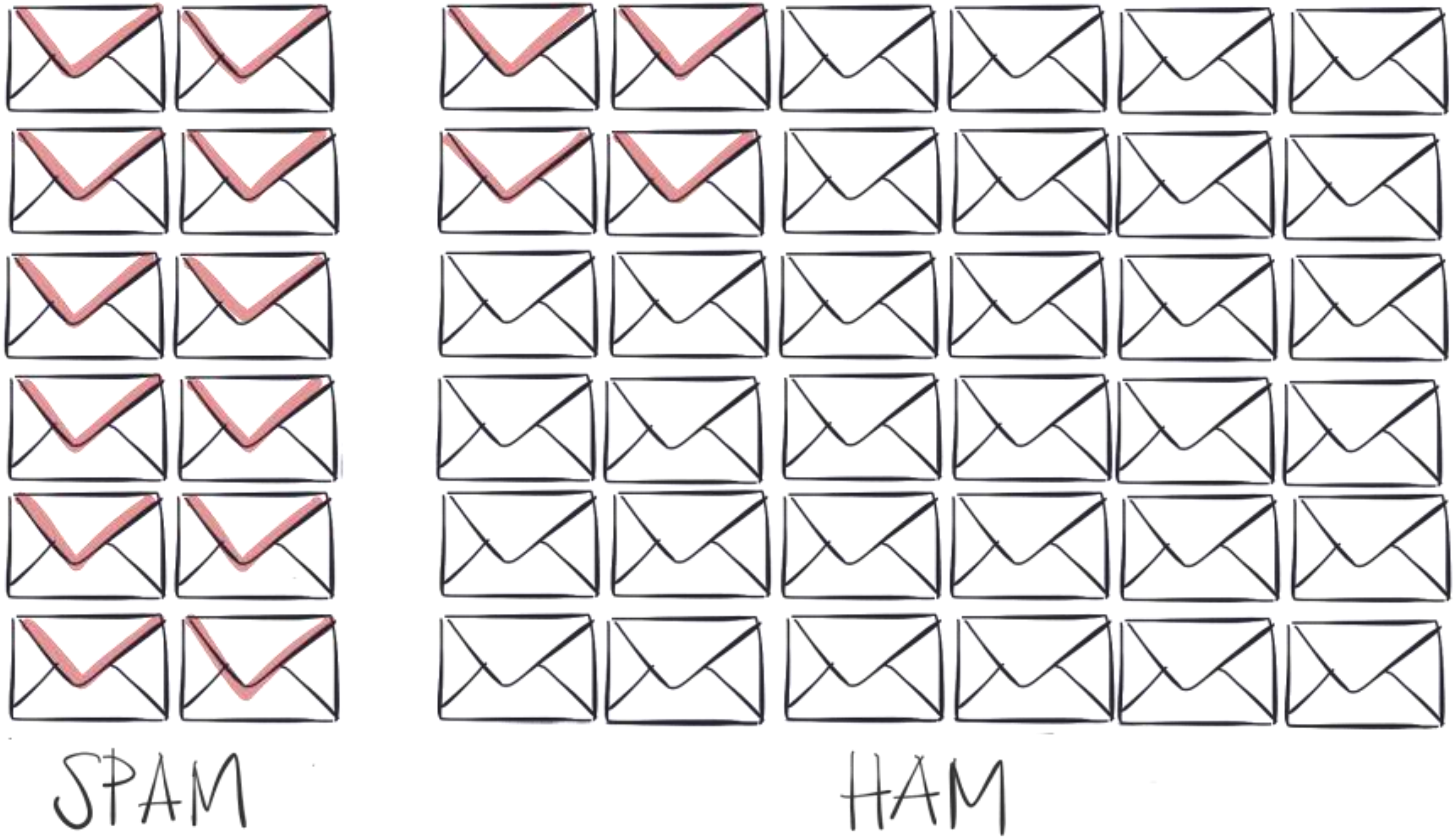
HAM OR SPAM?



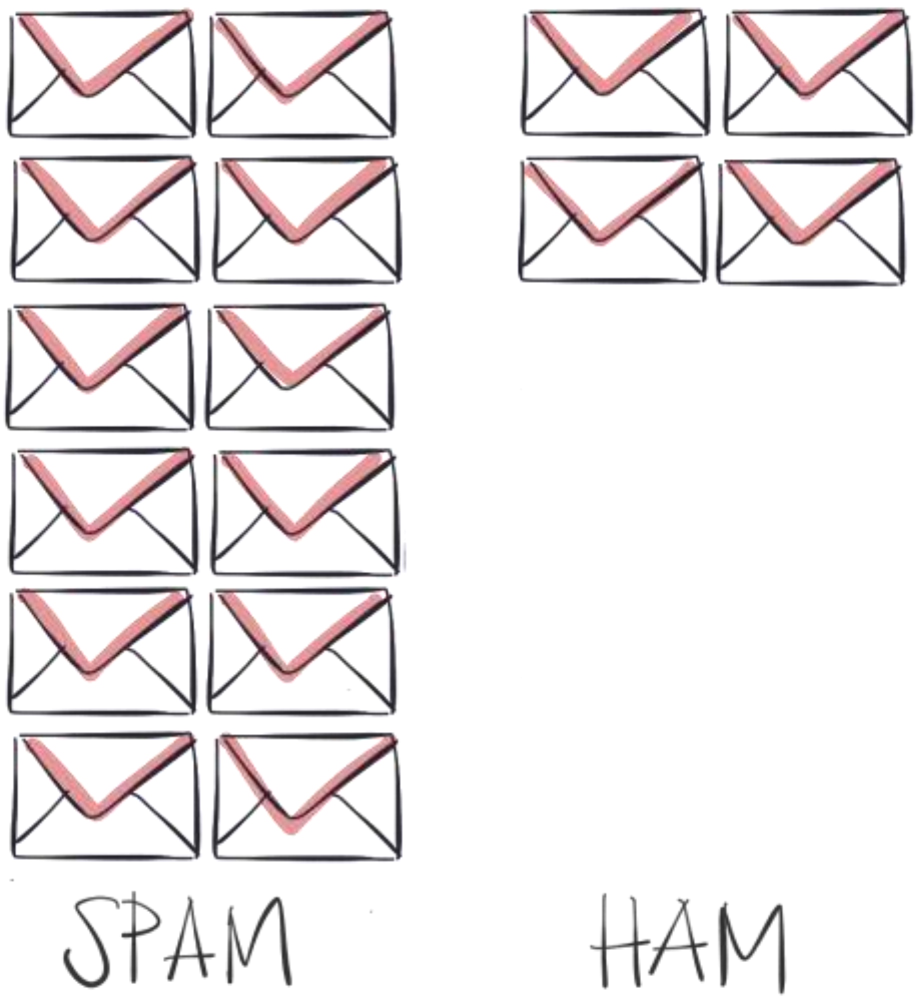
HAM OR SPAM?



HAM OR SPAM?



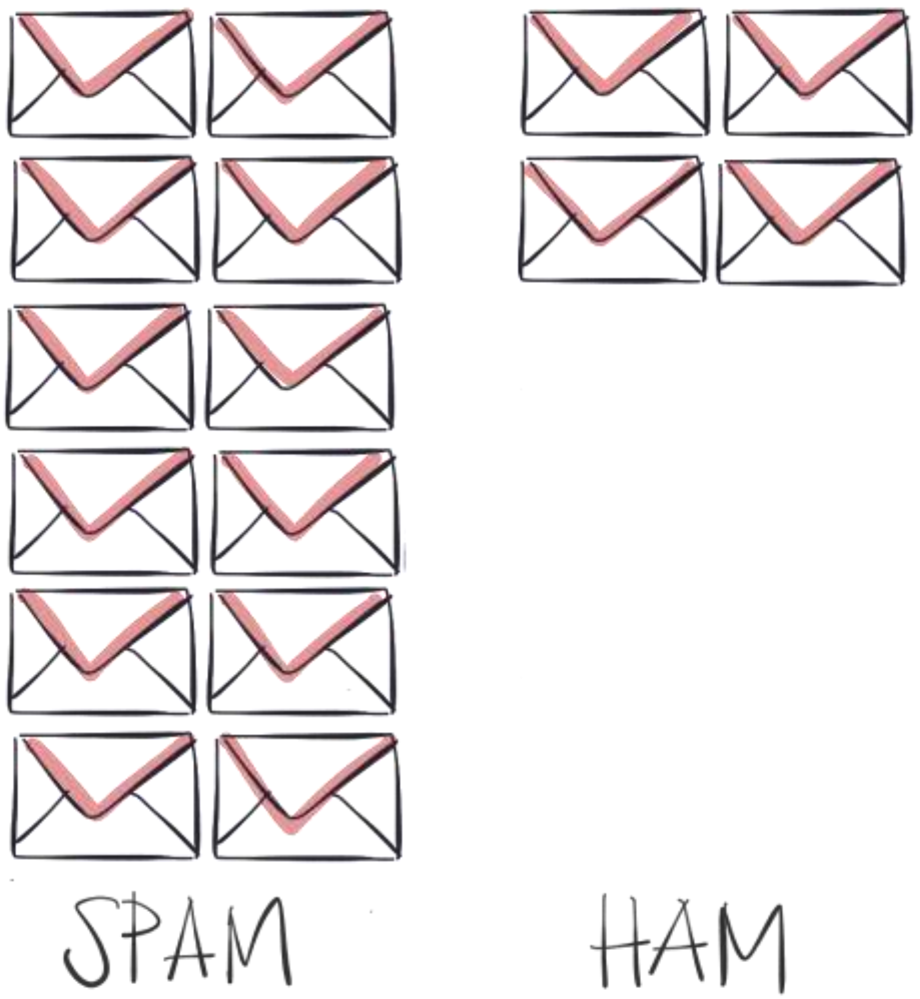
HAM OR SPAM?



SPELLING MISTAKE

40% 75% 90%

HAM OR SPAM?



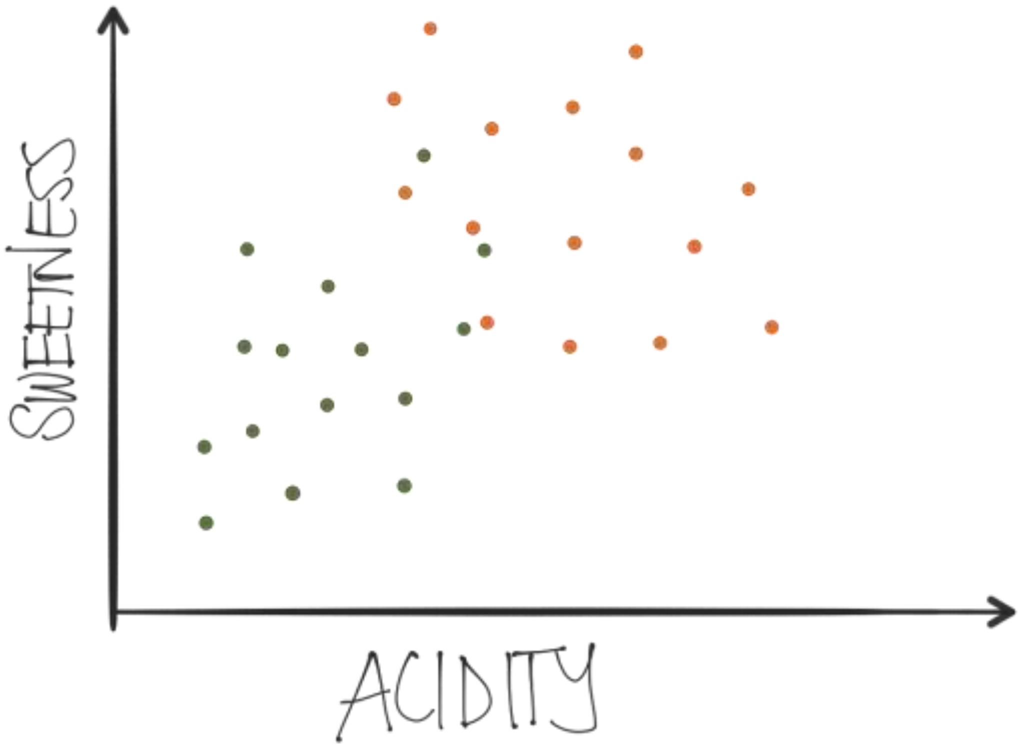
SPELLING MISTAKE 75%

CHEAP 80%

NO TITLE 70%

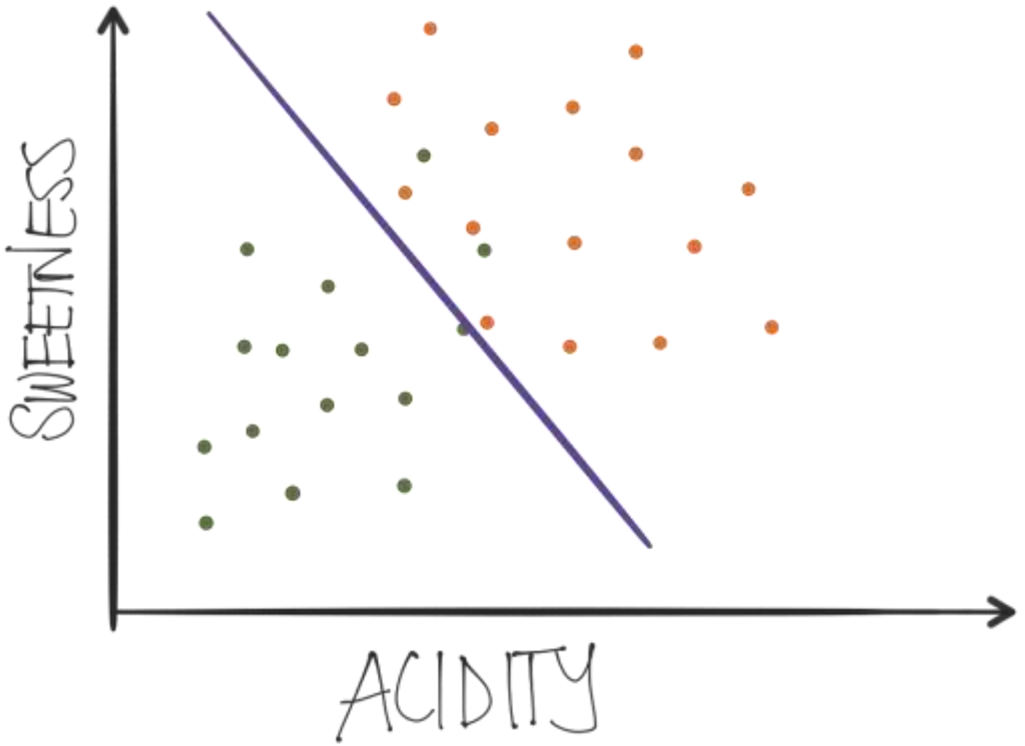
[NAIVE BAYES]

APPLES OR ORANGES



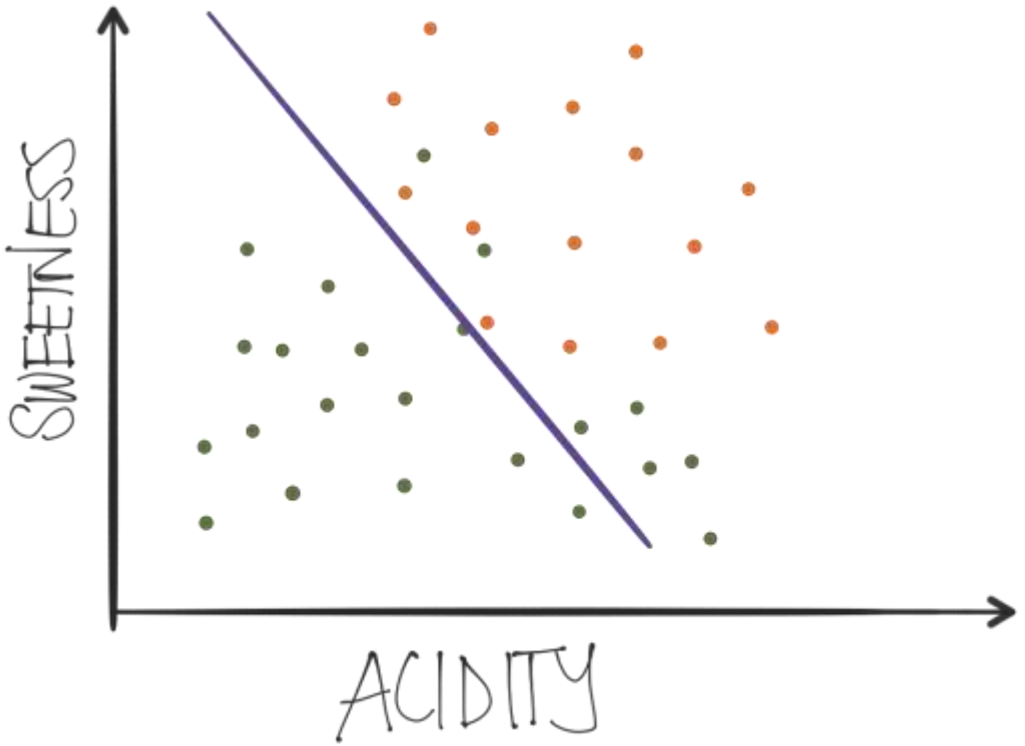
[LOGISTIC REGRESSION]

APPLES OR ORANGES

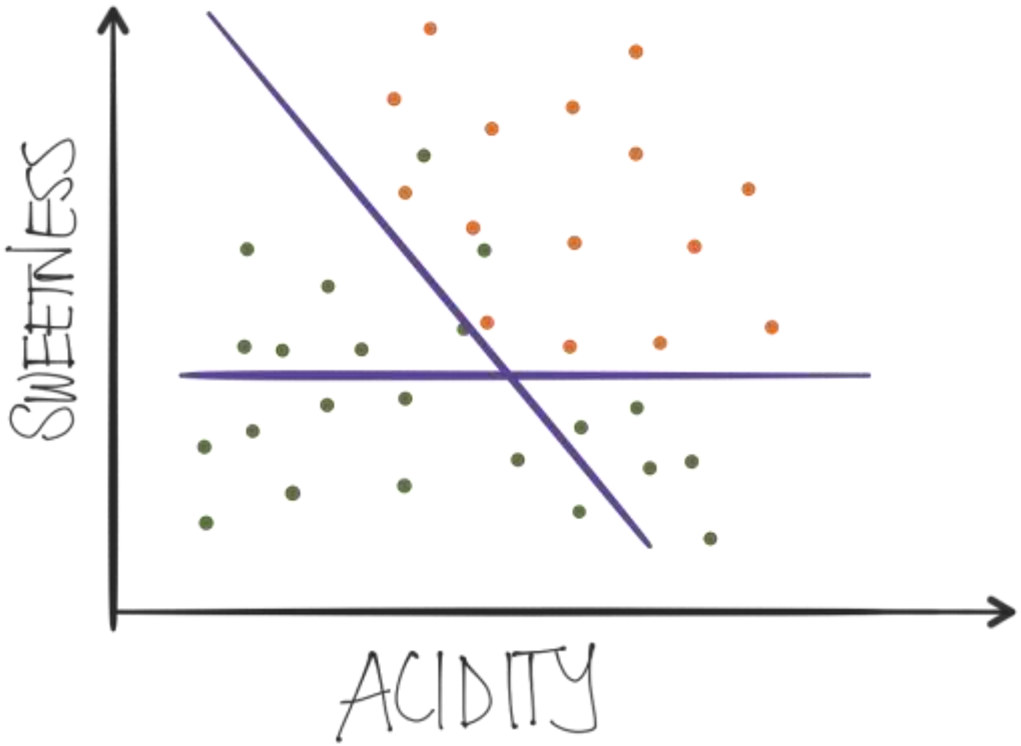


[LOGISTIC REGRESSION]

APPLES OR ORANGES

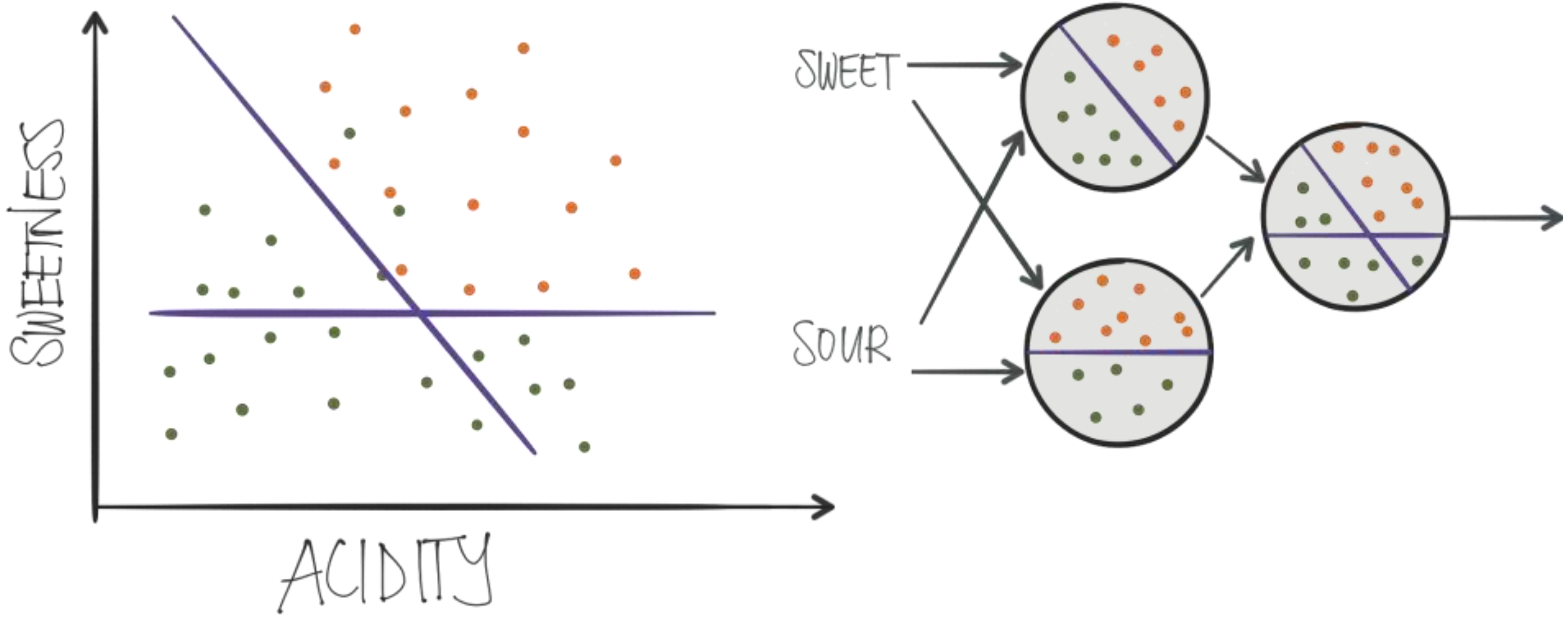


APPLES OR ORANGES

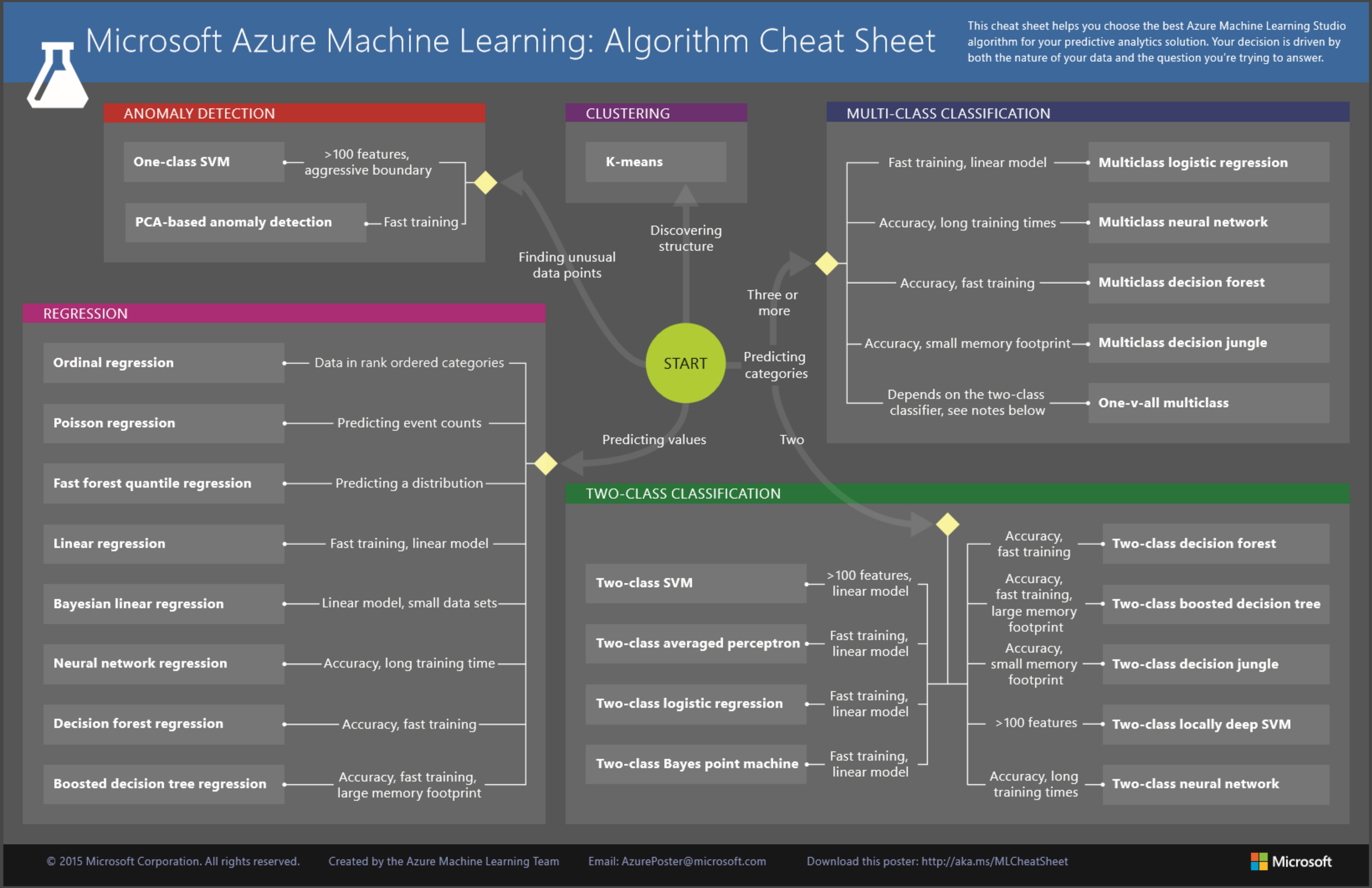


[NEURAL NET]

APPLES OR ORANGES



[NEURAL NET]



Microsoft Azure Machine Learning: Algorithm Cheat Sheet
This cheat sheet helps you choose the best Azure Machine Learning Studio algorithm for your predictive analytics solution. Your decision is driven by both the nature of your data and the question you're trying to answer.
ANOMALY DETECTION
One-class SVM
>100 features, aggressive boundary
PCA-based anomaly detection
Fast training
CLUSTERING
K-means
Discovering structure
Finding unusual data points
MULTI-CLASS CLASSIFICATION
Fast training, linear model
Multiclass logistic regression
Accuracy, long training times
Multiclass neural network
Accuracy, fast training
Multiclass decision forest
Accuracy, small memory footprint
Multiclass decision jungle
Depends on the two-class classifier, see notes below
One-v-all multiclass
Three or more
START
Predicting categories
Two
Predicting values
REGRESSION
Ordinal regression
Data in rank ordered categories
Poisson regression
Predicting event counts
Fast forest quantile regression
Predicting a distribution
Linear regression
Fast training, linear model
Bayesian linear regression
Linear model, small data sets
Neural network regression
Accuracy, long training time
Decision forest regression
Accuracy, fast training
Boosted decision tree regression
Accuracy, fast training, large memory footprint
TWO-CLASS CLASSIFICATION
Two-class SVM
>100 features, linear model
Two-class averaged perceptron
Fast training, linear model
Two-class logistic regression
Fast training, linear model
Two-class Bayes point machine
Fast training, linear model
Accuracy, fast training
Two-class decision forest
Accuracy, fast training, large memory footprint
Two-class boosted decision tree
Accuracy, small memory footprint
Two-class decision jungle
>100 features
Two-class locally deep SVM
Accuracy, long training times
Two-class neural network
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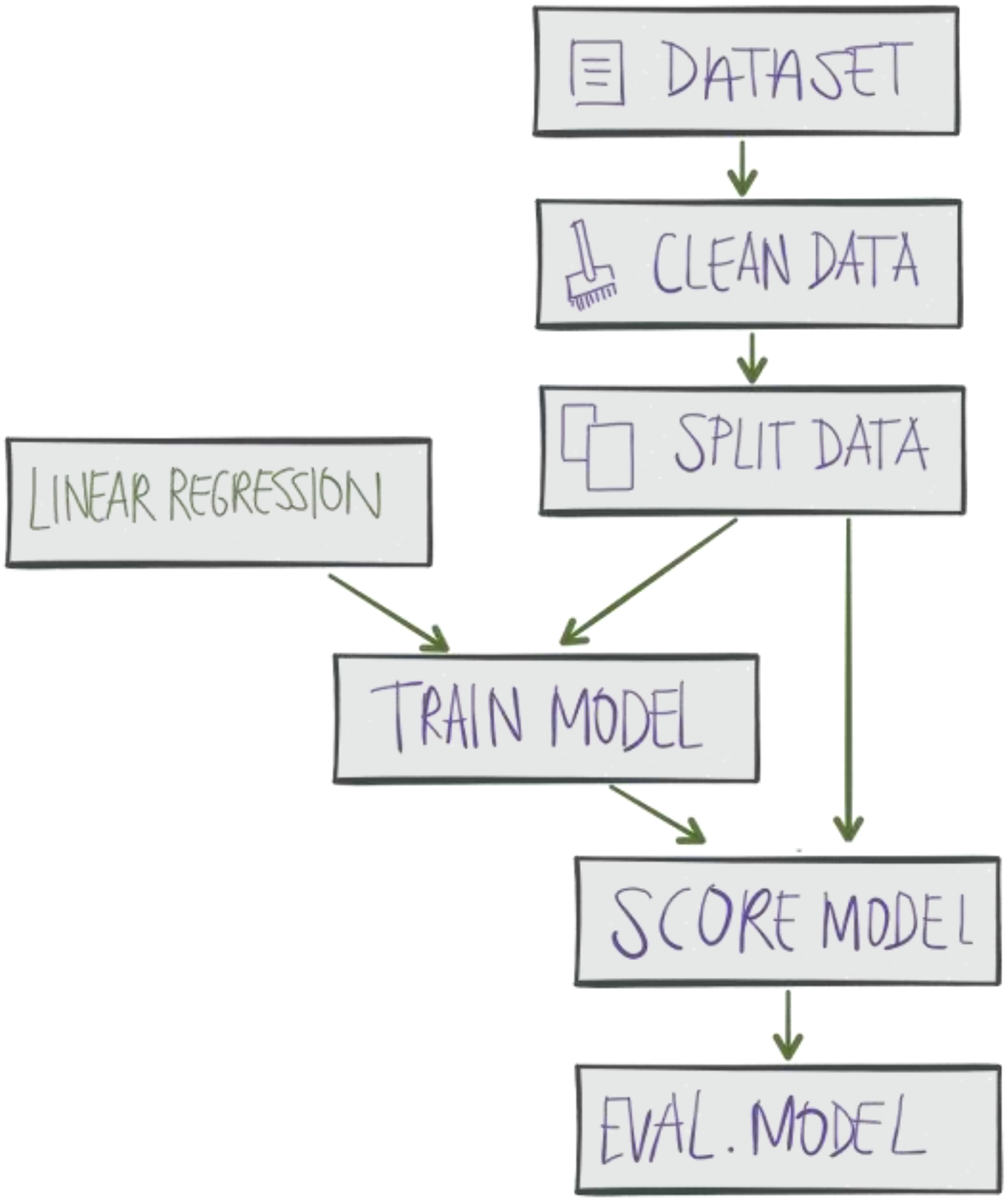
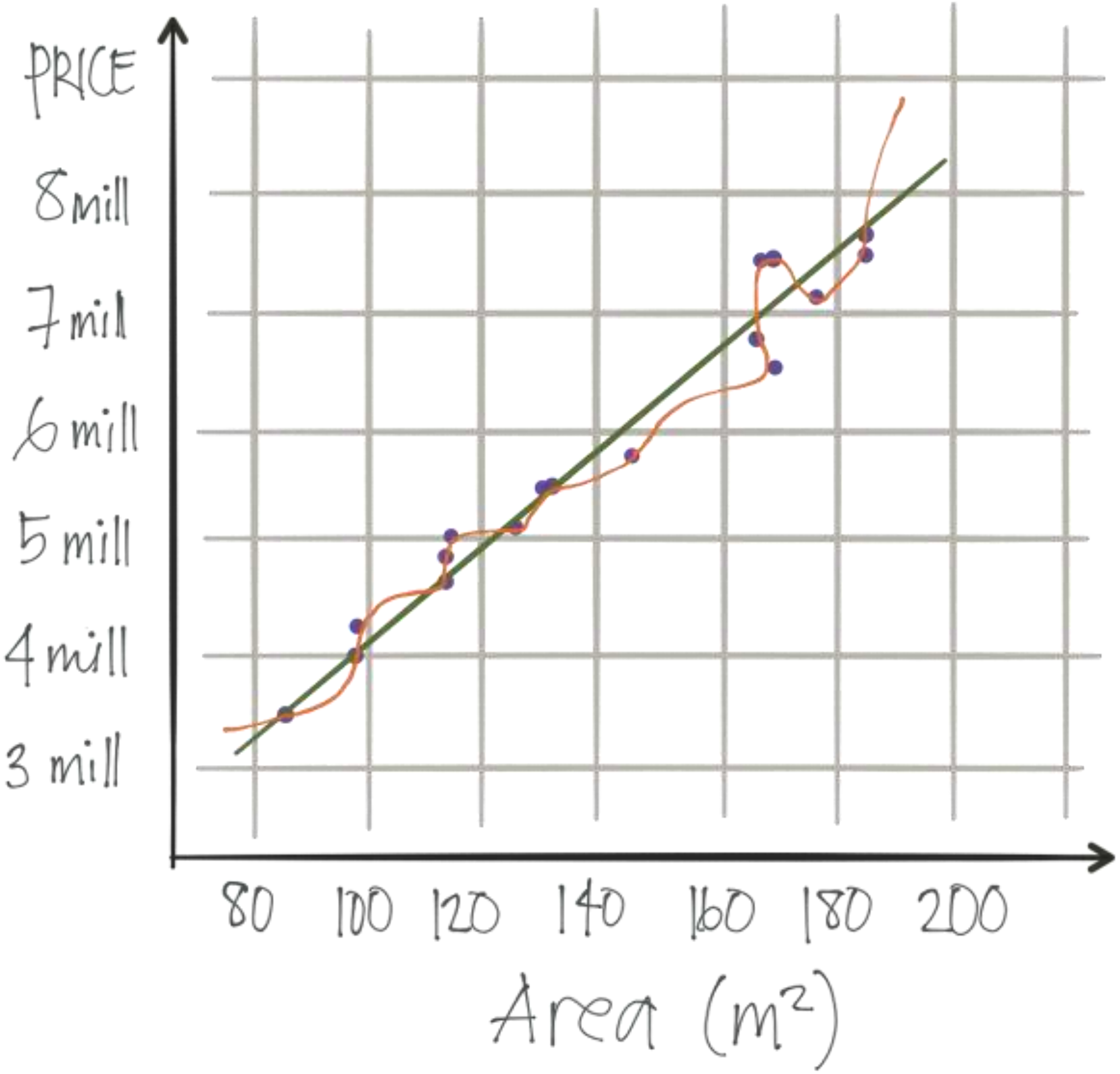
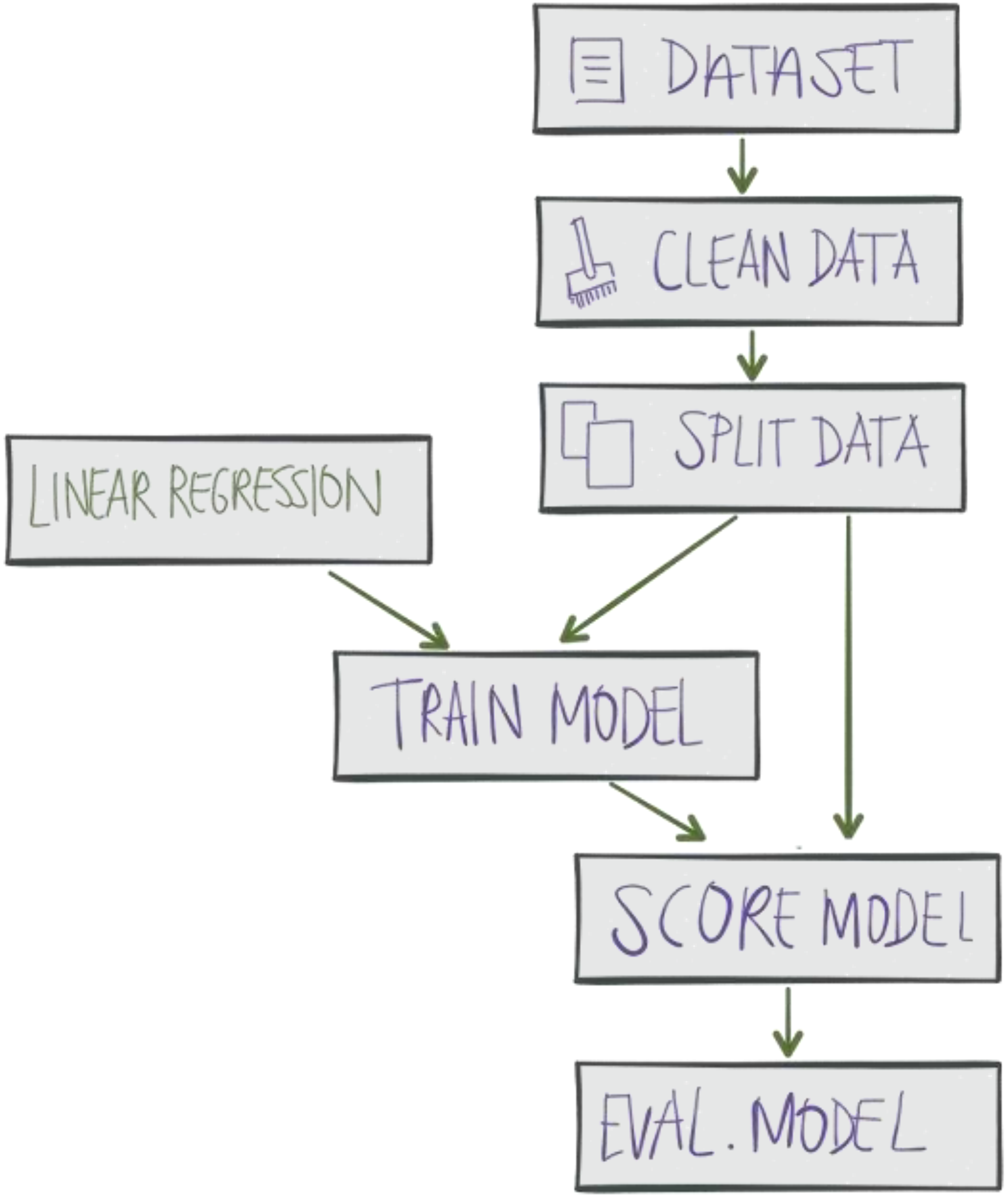
Created by the Azure Machine Learning Team
Email: AzurePoster@microsoft.com
Download this poster: http://aka.ms/MLCheatSheet
Microsoft

TRAIN THE MODEL

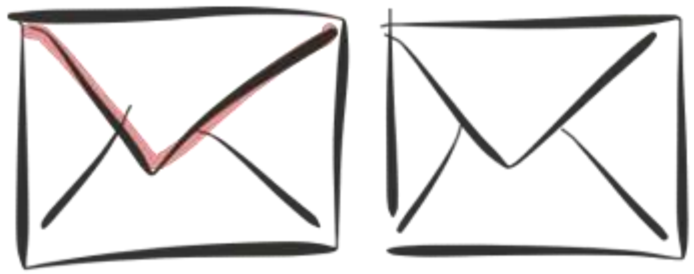

DATASET
CLEAN DATA
SPLIT DATA
LINEAR REGRESSION
TRAIN MODEL
SCORE MODEL
EVAL. MODEL

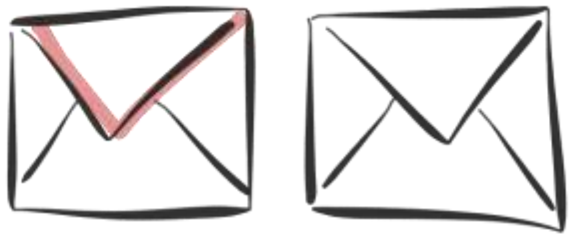
AREA m^2	PRICE kkr
134	5 495
115	4 700
167	7 500
185	7775
84	3500
98	4000~~0~~
115	4 850
185	7500
164	6900
145	5950
123	5010
128	5600
167	6750
115	5000
178	7200
97	4290




DATASET
CLEAN DATA
SPLIT DATA
LINEAR REGRESSION
TRAIN MODEL
SCORE MODEL
EVAL. MODEL

HOW GOOD IS MY MODEL





PREDICTION

ACTUAL	TO SPAM	TO INBOX	
SPAM	100	170	270
HAM	30	700	
	130		

ACCURACY

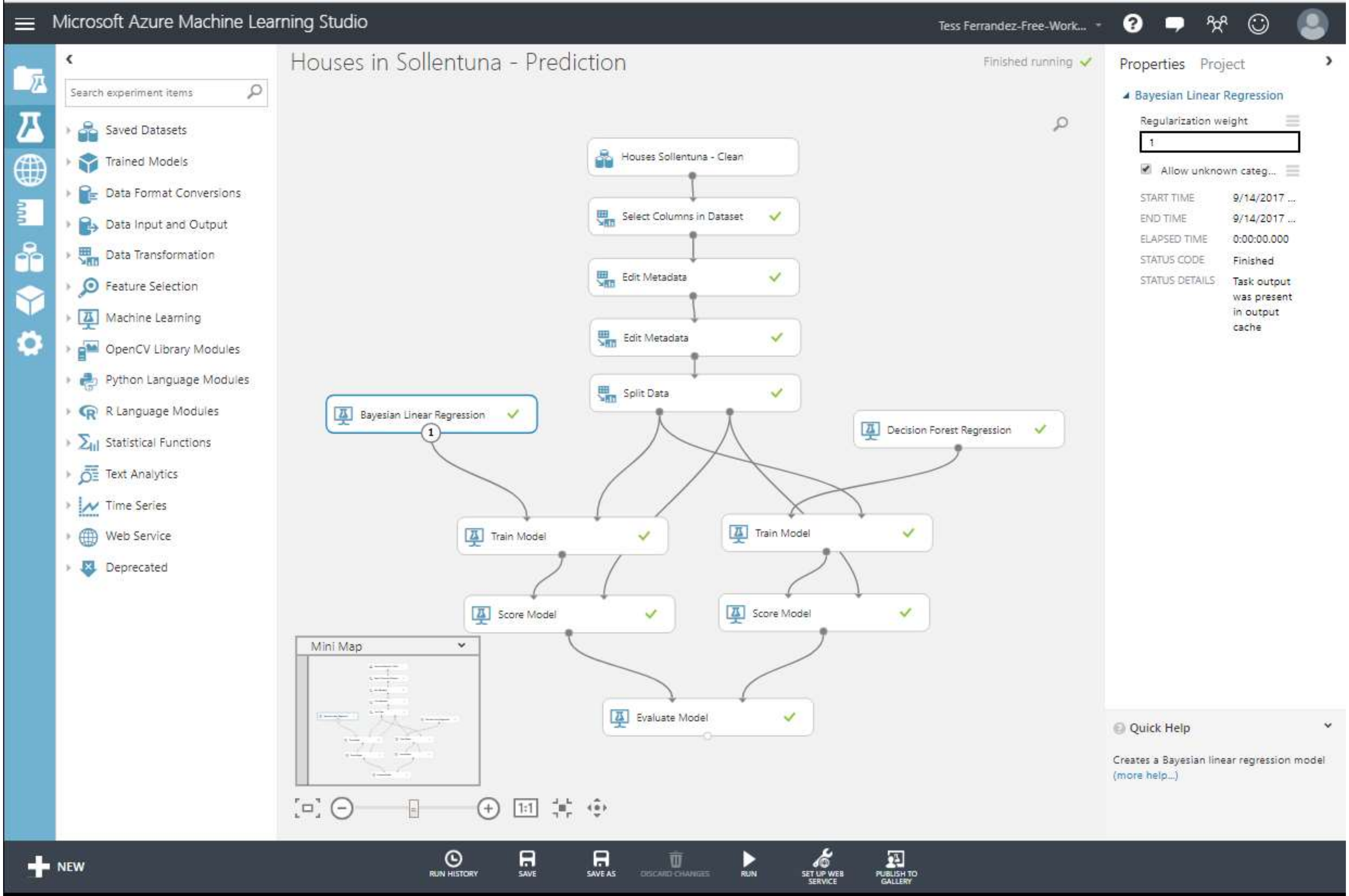
800/1000 = 80%

PRECISION

100 / 130 = 76.9%

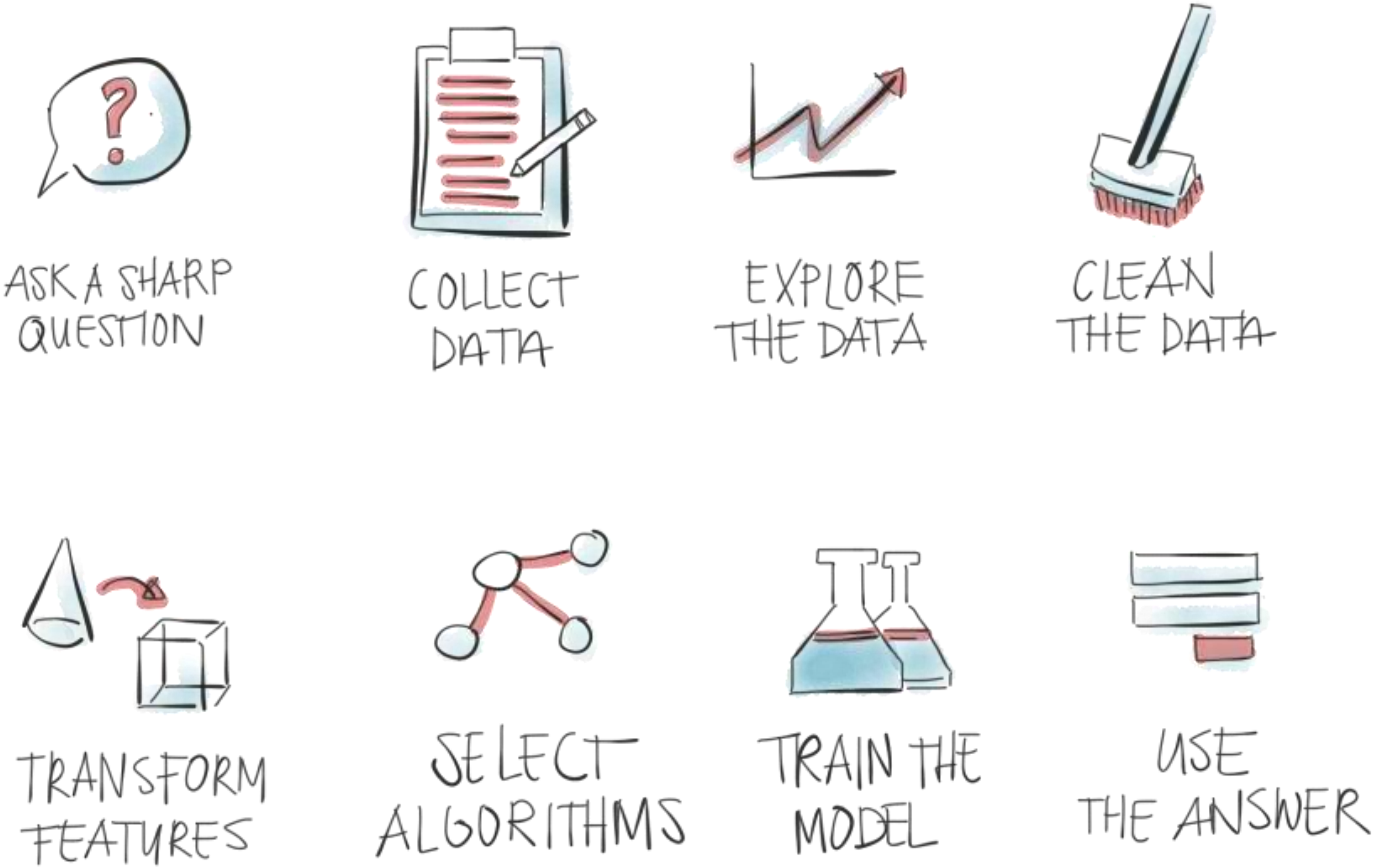
RECALL

100 / 270 = 37%



Microsoft Azure Machine Learning Studio
Tess Ferrandez-Free-Work...
Houses in Sollentuna - Prediction
Finished running
Search experiment items
Saved Datasets
Trained Models
Data Format Conversions
Data Input and Output
Data Transformation
Feature Selection
Machine Learning
OpenCV Library Modules
Python Language Modules
R Language Modules
Statistical Functions
Text Analytics
Time Series
Web Service
Deprecated
Houses Sollentuna - Clean
Select Columns in Dataset
Edit Metadata
Edit Metadata
Split Data
Bayesian Linear Regression
Decision Forest Regression
Train Model
Train Model
Score Model
Score Model
Evaluate Model
Mini Map
Properties
Project
Bayesian Linear Regression
Regularization weight
1
Allow unknown categ...
START TIME
9/14/2017 ...
END TIME
9/14/2017 ...
ELAPSED TIME
0:00:00.000
STATUS CODE
Finished
STATUS DETAILS
Task output was present in output cache
Quick Help
Creates a Bayesian linear regression model
(more help...)
NEW
RUN HISTORY
SAVE
SAVE AS
DISCARD CHANGES
RUN
SET UP WEB SERVICE
PUBLISH TO GALLERY

USE
THE ANSWER


ASK A SHARP QUESTION
COLLECT DATA
EXPLORE THE DATA
CLEAN THE DATA
TRANSFORM FEATURES
SELECT ALGORITHMS
TRAIN THE MODEL
USE THE ANSWER

A

DEVELOPERS GUIDE TO

MACHINE LEARNING

@TESSFERRANDEZ