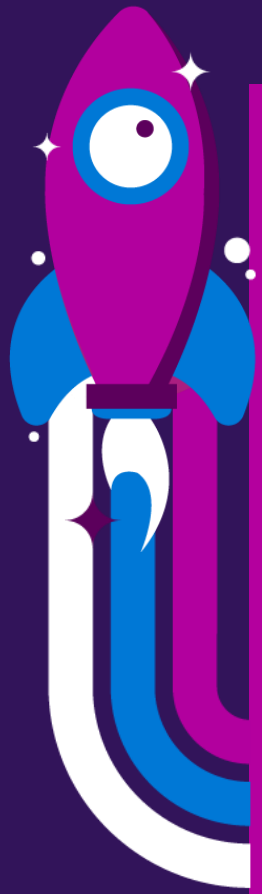


Microsoft

MACHINE LEARNING

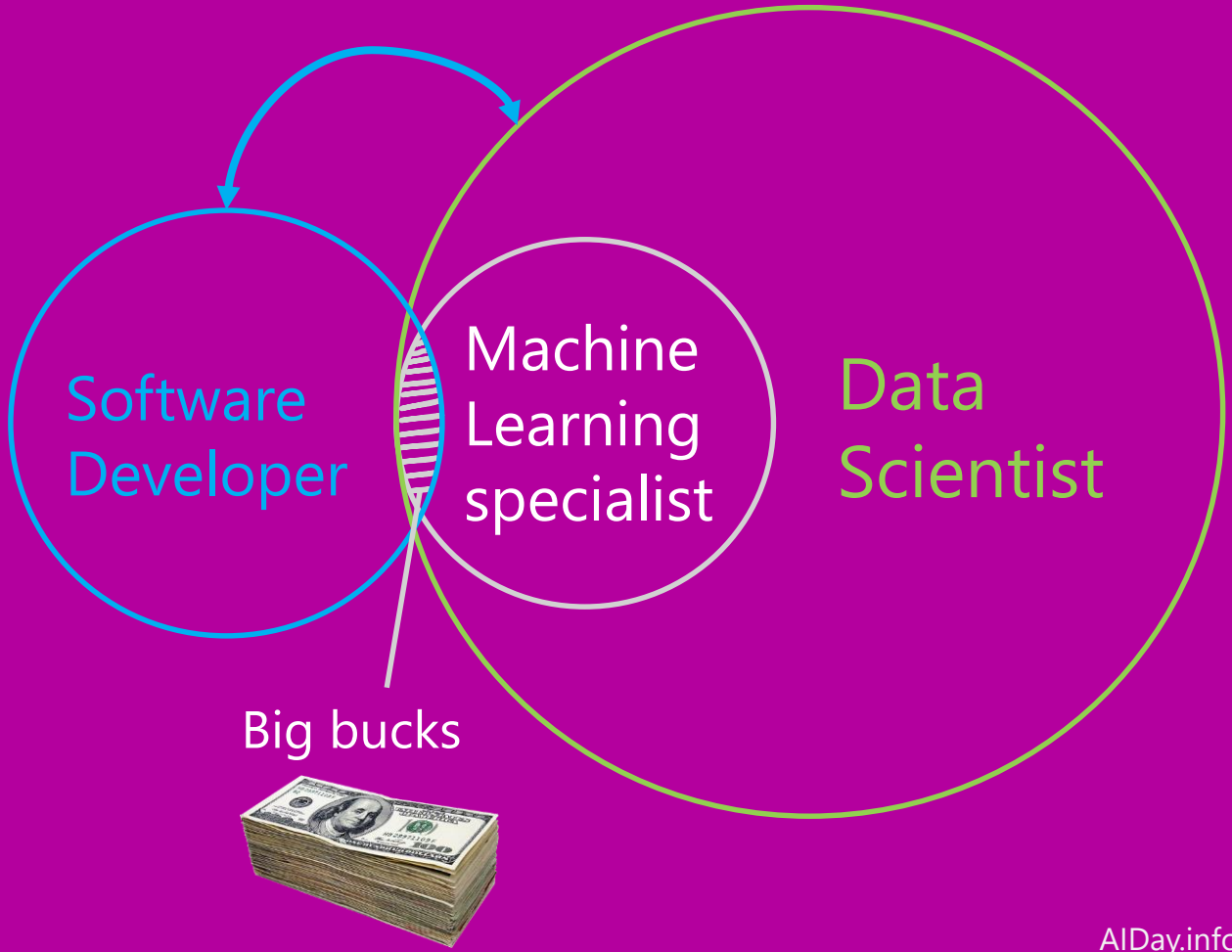
Andrew Fryer, @DeepFat

WHO ARE YOU?

Mathematician?

Data scientist?

Developer first?


Software Developer
Machine Learning specialist
Data Scientist
Big bucks

I'M JUST A DEVELOPER!

AN ML TOOL SHOULD…

- Forget about fine detail
- Embed ML in my application
- Retain power

Azure Machine Learning Studio

studio.azureml.net

Design

Train

Deploy

WHY ALL THE FUSS ABOUT MACHINE LEARNING?

Collaborative filtering optimization objective

→ Given $x^{(1)}, \ldots, x^{(n_m)}$, estimate $\theta^{(1)}, \ldots, \theta^{(n_u)}$:

$$\min_{\theta^{(1)},\ldots,\theta^{(n_u)}} \frac{1}{2} \sum_{j=1}^{n_u} \sum_{i:r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)})^2 + \frac{\lambda}{2} \sum_{j=1}^{n_u} \sum_{k=1}^{n} (\theta_k^{(j)})^2$$

→ Given $\theta^{(1)}, \ldots, \theta^{(n_u)}$, estimate $x^{(1)}, \ldots, x^{(n_m)}$:

$$\min_{x^{(1)},\ldots,x^{(n_m)}} \frac{1}{2} \sum_{i=1}^{n_m} \sum_{j:r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)})^2 + \frac{\lambda}{2} \sum_{i=1}^{n_m} \sum_{k=1}^{n} (x_k^{(i)})^2$$

Minimizing $x^{(1)}, \ldots, x^{(n_m)}$ and $\theta^{(1)}, \ldots, \theta^{(n_u)}$ simultaneously:

$$J(x^{(1)}, \ldots, x^{(n_m)}, \theta^{(1)}, \ldots, \theta^{(n_u)}) = \frac{1}{2} \sum_{(i,j):r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)})^2 + \frac{\lambda}{2} \sum_{i=1}^{n_m} \sum_{k=1}^{n} (x_k^{(i)})^2 + \frac{\lambda}{2} \sum_{j=1}^{n_u} \sum_{k=1}^{n} (\theta_k^{(j)})^2$$

$$\min_{\substack{x^{(1)},\ldots,x^{(n_m)} \\ \theta^{(1)},\ldots,\theta^{(n_u)}}} J(x^{(1)}, \ldots, x^{(n_m)}, \theta^{(1)}, \ldots, \theta^{(n_u)})$$

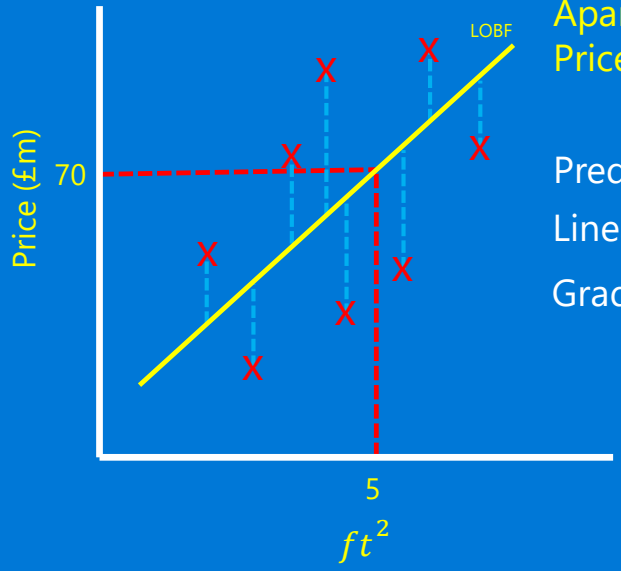
VERY HELPFUL NOT SCARY MATHS

2 minute primer

Supervised
- Classification
- Regression
- Anomaly detection

Unsupervised
- Clustering

Reinforcement
- Agent based learning



Apartment in London = $5ft^2$
Price = £70 million

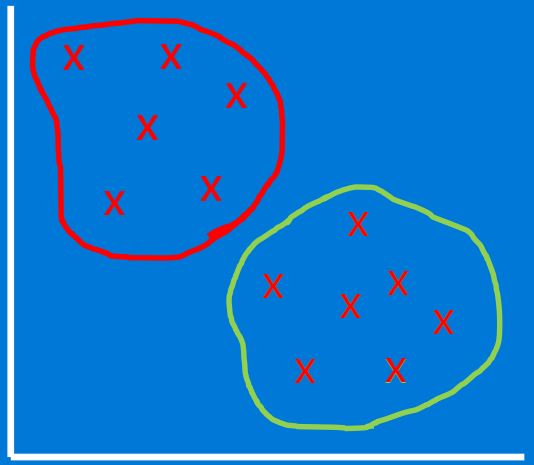
Predict the future

Linear **regression**

Gradient descent

= People who panic buy after a few inches of snow

= Sane people



Gain new insight

Unsupervised

Clustering

MACHINES ARE BETTER THAN HUMANS

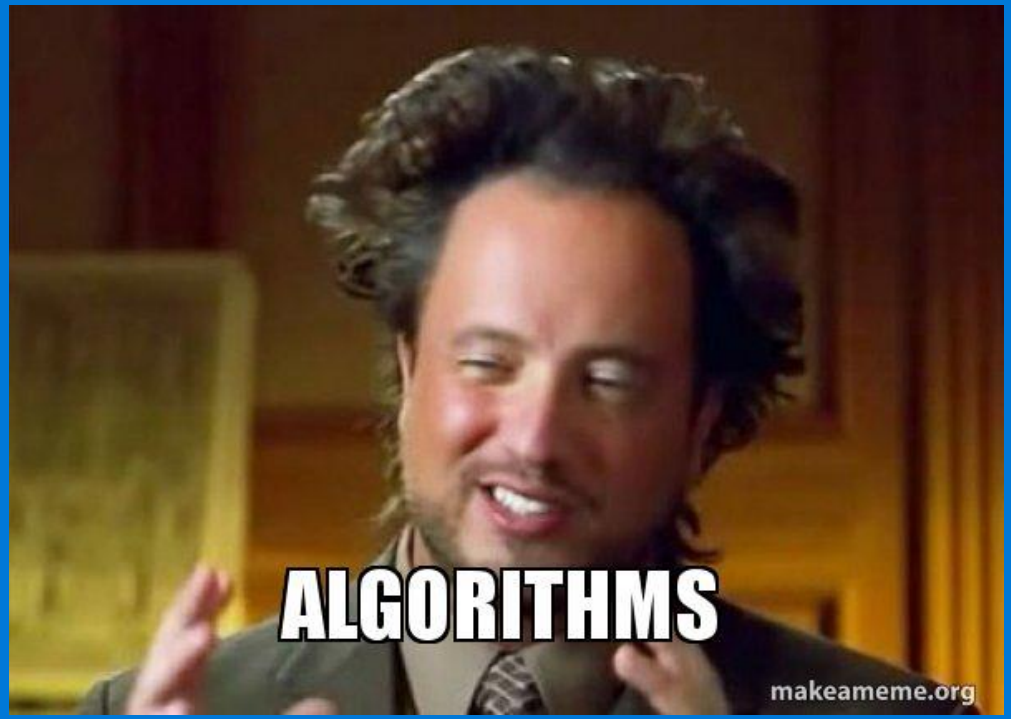
£1000+ USA RUS 20’s

Name	Amount	Issued	Used	Age	Fraudulent
Smith	£2600.45	USA	USA	22	No
Paul	£2294.58	USA	RUS	29	Yes
Peters	£1003.30	USA	RUS	25	Yes
Adams	£8488.32	FRA	USA	64	No
Pali	£200.12	AUS	JAP	58	No
Jones	£3250.11	USA	RUS	43	No
Hanford	£8156.20	USA	RUS	27	Yes
Marx	£7457.11	UK	GER	32	No
Norse	£540.00	USA	RUS	27	No
Edson	£7475.11	USA	RUS	20	Yes

WHAT ARE THE PATTERNS?

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1048488	2013	6	20	4	WN	13204	12889	740	0	0	920	0	0	0
1048489	2013	6	20	4	WN	13204	13198	920	-5	0	1105	-7	0	0
1048490	2013	6	20	4	WN	13204	13232	2050	19	1	2230	9	0	0
1048491	2013	6	20	4	WN	13204	13232	655	-2	0	840	10	0	0
1048492	2013	6	20	4	WN	13204	13232	1005	8	0	1145	5	0	0
1048493	2013	6	20	4	WN	13204	13232	1655	9	0	1840	-5	0	0
1048494	2013	6	20	4	WN	13204	13232	1410	1	0	1555	-9	0	0
1048495	2013	6	20	4	WN	13204	13232	1850	25	1	2035	19	1	0
1048496	2013	6	20	4	WN	13204	13342	1400	-2	0	1550	-4	0	0
1048497	2013	6	20	4	WN	13204	13495	850	4	0	930	0	0	0
1048498	2013	6	20	4	WN	13204	13495	1105	7	0	1145	31	1	0
1048499	2013	6	20	4	WN	13204	13495	650	-2	0	725	-3	0	0
1048500	2013	6	20	4	WN	13204	13495	1725	72	1	1810	94	1	0
1048501	2013	6	20	4	WN	13204	13931	2100	5	0	2250	-6	0	0
1048502	2013	6	20	4	WN	13204	13931	1045	0	0	1240	-9	0	0
1048503	2013	6	20	4	WN	13204	14100	2045	28	1	2310	18	1	0
1048504	2013	6	20	4	WN	13204	14100	845	-1	0	1110	-15	0	0
1048505	2013	6	20	4	WN	13204	14107	1905	51	1	2025	40	1	0
1048506	2013	6	20	4	WN	13204	14122	910	-6	0	1125	-4	0	0
1048507	2013	6	20	4	WN	13204	14122	2020	28	1	2230	32	1	0
1048508	2013	6	20	4	WN	13204	14307	2130	25	1	15	10	0	0
1048509	2013	6	20	4	WN	13204	14307	1010	6	0	1250	4	0	0
1048510	2013	6	20	4	WN	13204	14307	850	3	0	1135	-12	0	0
1048511	2013	6	20	4	WN	13204	14307	1425	1	0	1710	7	0	0
1048512	2013	6	20	4	WN	13204	14492	1030	-3	0	1205	-6	0	0
1048513	2013	6	20	4	WN	13204	14683	1750	84	1	1935	78	1	0
1048514	2013	6	20	4	WN	13204	14683	1155	6	0	1340	12	0	0
1048515	2013	6	20	4	WN	13204	14730	1700	89	1	1905	103	1	0
1048516	2013	6	20	4	WN	13204	14843	2105	14	0	2355	6	0	0
1048517	2013	6	20	4	WN	13204	14843	1325	99	1	1615	88	1	0
1048518	2013	6	20	4	WN	13204	14843	650	1	0	935	-1	0	0
1048519	2013	6	20	4	WN	13204	14843	1115	3	0	1405	-3	0	0
1048520	2013	6	20	4	WN	13204	15016	1830	22	1	1950	55	1	0
1048521	2013	6	20	4	WN	13204	15016	1005	16	1	1130	10	0	0
1048522	2013	6	20	4	WN	13232	10140	1000	7	0	1155	-1	0	0

HOW?



$repeat\ until\ convergence\{$

$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \theta_1, \ldots, \theta_1)$ or for short $\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$

$\}$ (simultaneously update for every $j = 0, \ldots, n$)

What's that?

Translation:

```
for(j = 0; j<n; j++){

        theta[j] = Math.something();
};
```

GRADIENT DESCENT FOR MULTIVARIATE LINEAR REGRESSION

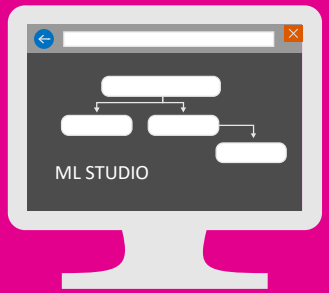
DON’T BELIEVE THE HYPE

Data

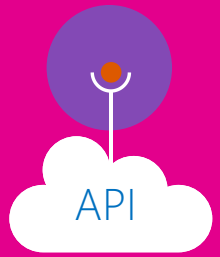
Blobs and Tables

Hadoop (HDInsight)

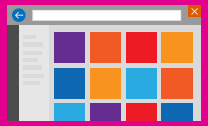
Relational DB (Azure SQL DB)



Integrated development environment for Machine Learning

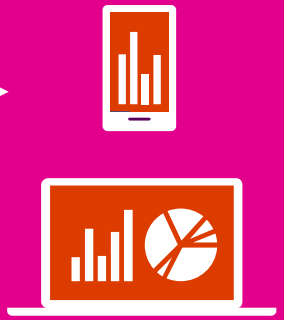


Model is now a web service that is callable



Monetize the API through our marketplace

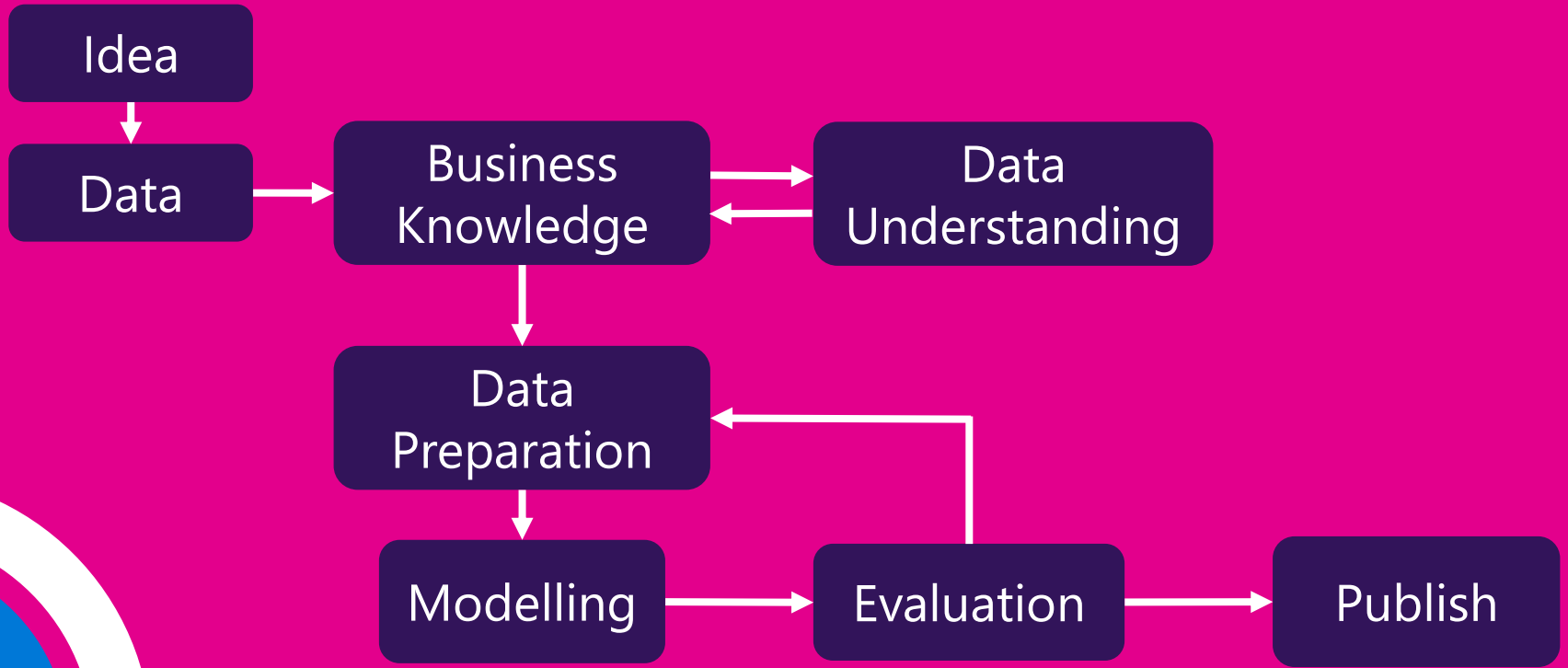
Clients



Credit: Amy Boyd, @AmyKateNicho

Microsoft

AZURE ML PROCESS MODEL



Credit: Amy Boyd, @AmyKateNicho

DEMO

MACHINE LEARNING LAB

CONTACT ME

ANDREW FRYER

http://deepfat.me

@DeepFat

9:00	**The Microsoft AI Platform**	Martin
9:45	**Computer Vision Services**	Frances
10:30	Break	
10:45	**Bots & Conversational Apps**	Jamie
11:45	**Knowledge Services**	Martin
12:30	Lunch	
13:15	**Language & Speech Services**	Frances & Jamie
14:00	**Machine Learning**	Andrew
14:45	**Summary & Envisioning Intro**	Martin
15:00	Break	
15:15	**Envisioning**	Groups
17:00	Close	