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#ODSC

BOSTON 2015

@opendatasci

FEATURE ENGINEERING

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#ODSC, @opendatasci

Talk Outline

- What is feature engineering?
- Limits on number of features
- How to select a “good” set of features
- Standard FE techniques

- TL;DR: As we get better and better models, focus shifts to what we put into them
- FE interacts with other key areas of DS

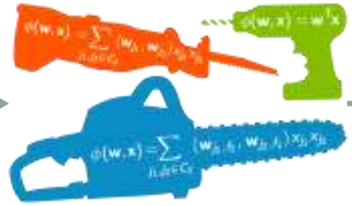
Feature Engineering

- (My) Definition: Transforming data to create model inputs.

Data Workflow

Raw Data

Data Cleaning



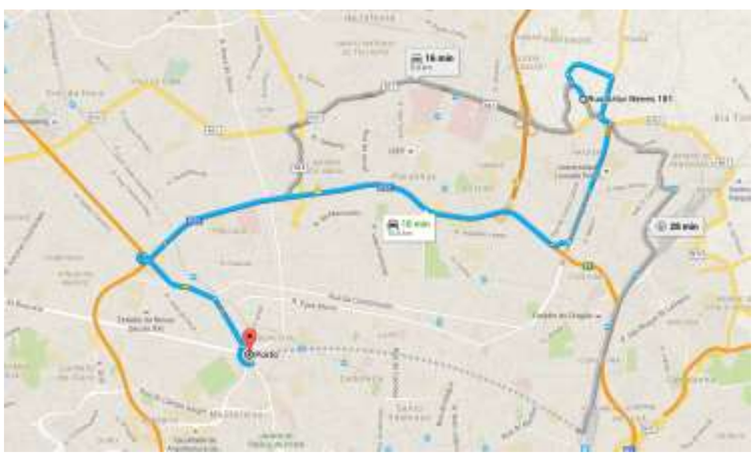
Feature Engineering

Model Building

Pre-Processing

Examples from Kaggle Competitions

Netflix

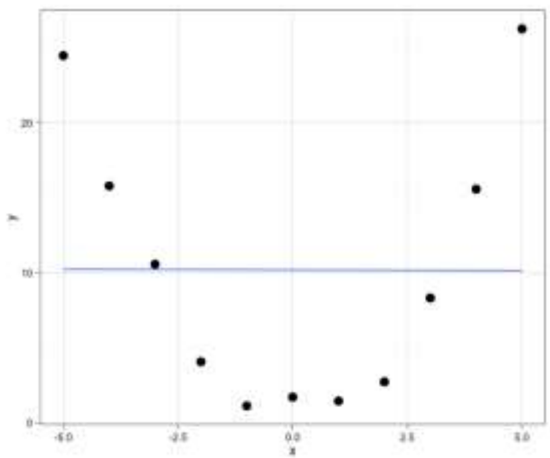


Portuguese Taxis

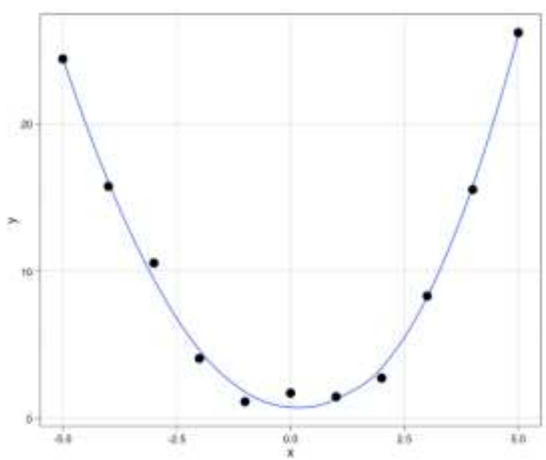
Titanic

“Golden Features”

How does it work?

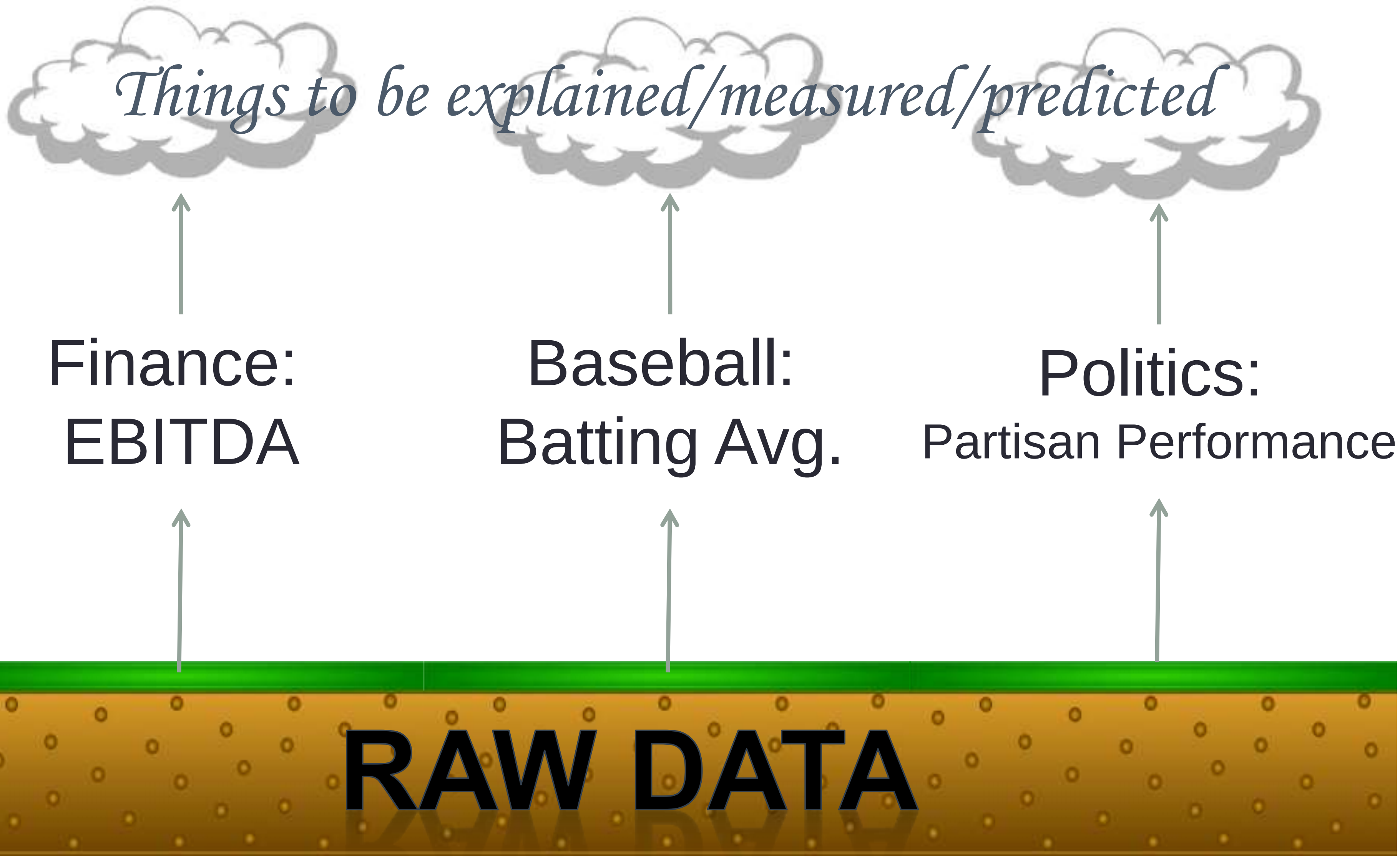


```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 10.17912    2.92472    3.48  0.00693 **
x           -0.00923    0.92488   -0.01  0.99225
---
Residual standard error: 9.7 on 9 degrees of freedom
Multiple R-squared: 1.107e-05, Adjusted R-squared: -0.11
F-statistic: 9.96e-05 on 1 and 9 DF,  p-value: 0.9923
```



```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.29879    0.48994    0.61    0.559
x           -0.00923    0.10256   -0.09    0.930
x2           0.98803    0.03672   26.91 3.92e-09 ***
---
Residual standard error: 1.076 on 8 degrees of freedom
Multiple R-squared: 0.9891, Adjusted R-squared: 0.9863
F-statistic: 362 on 2 and 8 DF, p-value: 1.427e-08
```

Features are engineered everywhere



The Big Questions

- Seen in this light, FE is ubiquitous (as all truly important concepts are)
- Any time you construct an intermediate variable, you're doing FE
- Two questions naturally arise:
  1. How do you construct "good" features?
  2. What are the limits on this process?
- I'll answer the second one first, because it's easier….

Limits on Feature Engineering

- In medical studies, social science, financial analysis, etc., two main problems emerge
- Eating up degrees of freedom: relatively small data sets
    - # of respondents in survey
    - # of patients in trial
    - # of elections to Congress
    - If your data lives in an *NxK* matrix, you want to make sure that *K* is small relative to *N*
- Relevance to hypothesis testing, emphasis on explanation
    - You generally start with an equation defining the relationship between the key independent and dependent variables
    - Other variables enter your model as controls, not really interested in their functional form

Limits on Feature Engineering

- In most modern data science applications, neither is an issue
  - We start with lots of data, and
  - Care more about prediction than explanation
- So why not add in lots of extra variables?
  - Think of your data not as what goes into your model, but a starting point for the cr n then be combined…

Limits on Feature Engineering

- First, adding many correlated predictors can decrease model performance
  - Adding an x^4 term to above example actually reduces model fit:

```
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.648123   0.628178   1.032 0.336513
x           -0.009230   0.103740  -0.089 0.931593
x2           0.866738   0.139087   6.232 0.000432 ***
x4           0.004852   0.005361   0.905 0.395572
---
Residual standard error: 1.088 on 7 degrees of freedom
Multiple R-squared:  0.9902,    Adjusted R-squared:  0.986
F-statistic: 236.1 on 3 and 7 DF,  p-value: 2.15e-07
```

- More variables make models less interpretable
- Models have to be generalizable to other data
  - Too much feature engineering can lead to overfitting
  - Close connection between feature engineering and cross-validation

How To Select a “Good” Set of Features

- This is <u>the</u> open-ended question in the field
- Separate (but related to) the question of feature selection – which variables to retain in a model.
- You can use some metrics to tell which features are useful, one at a time, like Pearson correlation coefficient
  - But this can’t tell you which <u>set</u> of features works best together
  - This is an NP complete problem, clearly too computationally hard
- Many new data analysis services include automated feature engineering as part of their packages
  - But if there are features you want in your model, it’s best to add them in explicitly, rather than depend on these generators.

A “Middle Theory” of FE

- Start with a reasonable-sized set of features
  - Include features suggested by domain knowledge
  - Test these out individually, build from the bottom up
- Number and type of features depend on model used
  - Can include more features if models does some feature selection
    - Lasso regression, e.g., logit with $||L_1||$ regularization (but not $||L_2||$ ridge)
    - GBM with backward pruning (but not random forests)
    - Stepwise regression, with either forward or backward feature selection
  - Some models are invariant to monotonic variable transformations
    - Tree-based approaches divide variables into two groups at each branch
- So, no perfect answer. But there are some standard techniques every data scientist should have in their bag of tricks.

Non-numeric to numeric

1. Count # of times each value appears

Zip Code	Count
10024	4
63105	2
94304	1
06443	3
10024	4
63105	2
06443	3
10024	4
10024	4
06443	3

Non-numeric to numeric

2. One-hot encoding

Religion	Catholic	Protestant	Jewish	Muslim
Catholic	1	0	0	0
Muslim	0	0	0	1
Jewish	0	0	1	0
Protestant	0	1	0	0
Catholic	1	0	0	0
Catholic	1	0	0	0
Jewish	0	0	1	0
Protestant	0	1	0	0
Muslim	0	0	0	1
Protestant	0	1	0	0

Non-numeric to numeric

3. The “hash trick”

string	h(string)
“The”	36
“quick”	8
“brown”	92
“fox”	14
“jumps”	75
“over”	25
“the”	36
“lazy”	44
“dog”	21

Non-numeric to numeric

4. Leave-one-out encoding

Single Variable Transformations

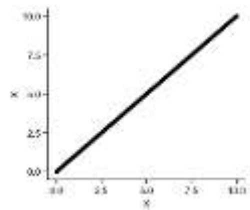
x

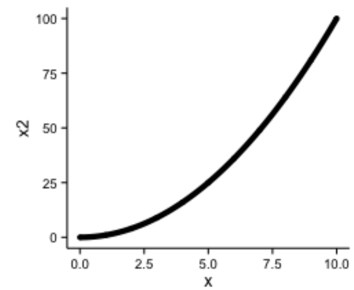
x^2

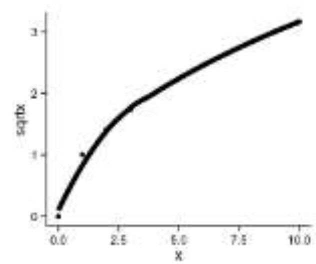
$$\sqrt{x}$$

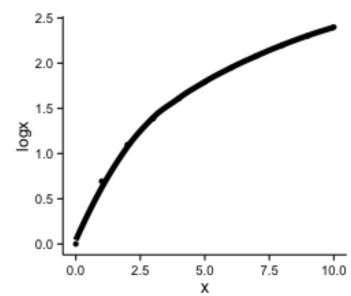
Log(x)

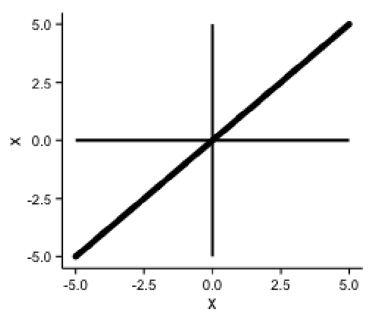
scaling











Two-variable combinations

1. Add: Sum similar-scaled variables

Q1	Q2	Q3	Q4	Total
33	88	51	81	251
11	11	72	30	124
15	36	70	55	176
70	82	8	50	209
99	56	35	86	276
7	20	10	71	107
65	0	25	74	164
96	25	2	89	211
60	29	56	92	238
63	50	96	61	269

Two-variable combinations

2. Subtract: Difference relative to baseline

ViewerID	MovieID	Date	Rating	Days Since First Rating
44972004	8825	1/1/13	5	0
44972004	0471	2/1/13	4	31
44972004	3816	3/1/13	5	59
44972004	8243	4/1/13	3	90
44972004	2855	5/1/13	5	120
44972004	9923	6/1/13	2	151
44972004	1023	7/1/13	4	181
44972004	8306	8/1/13	3	212
44972004	2771	9/1/13	2	243
44972004	5281	10/1/13	2	273

Two-variable combinations

3. Multiply: Interactive effects

ViewerID	Country	Domestic	DSFR	Dom*DSFR
8825	US	1	38	38
0471	CA	0	277	0
3816	FR	0	187	0
8243	US	1	33	33
2855	US	1	87	87
9923	GB	0	42	0
1023	IT	0	192	0
8306	CA	0	365	0
2771	US	1	505	505
5281	FI	0	49	0

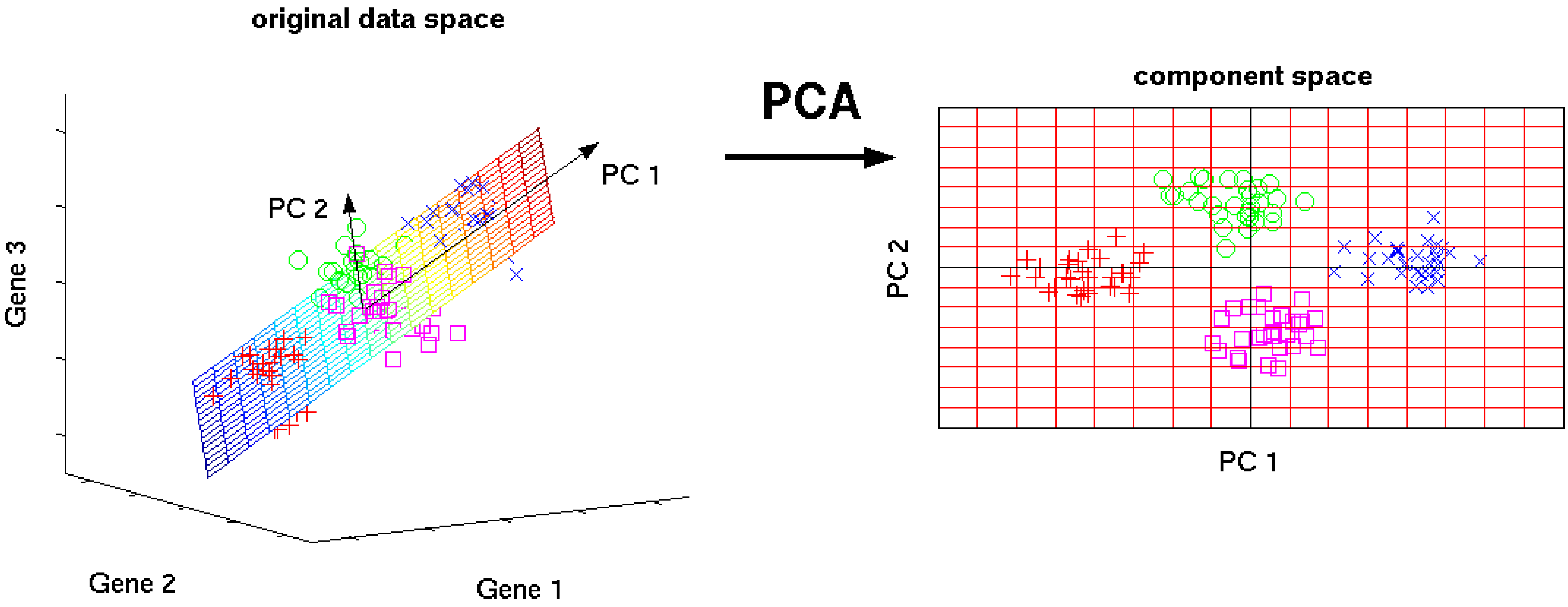
Two-variable combinations

4. Divide: Scaling/Normalizing

Country	GDP	Population	GDP/Capita
US	159849	275	581
CA	731812	111	6593
FR	826320	90	9181
IT	573494	80	7169
IR	609223	22	27692
GB	717673	60	11961
NE	605257	15	40350
MX	687944	124	5548
RU	203319	402	506
FI	744983	40	18625

Multivariate/Model-based Methods

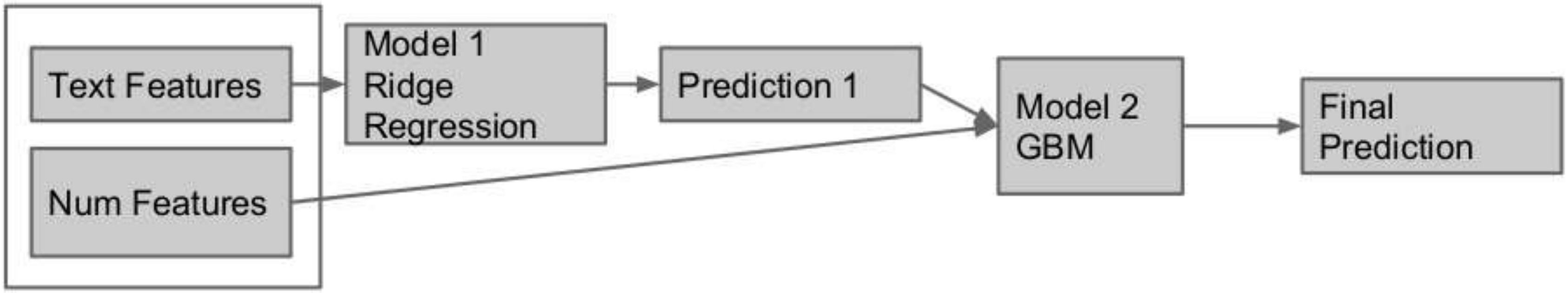
1. PCA/Factor Analysis/Clustering: Dimension reduction



Multivariate/Model-based Methods

2. Model Stacking: Outputs of one model are inputs to the next

- Do this, e.g., on half the data and use as input to the other half, and vice-versa



(Figure from Owen Zhang)

Conclusion

- Data science grew over the last decade due to improved modeling algorithms, better cross-validation procedures
- Now we have a number of good models, can get at problem from lots of different angles
- Most improvement will come from thinking carefully about what we put into our models = Feature Engineering
- This can be (semi-) automated, but it’s still one of the true arts of the profession
  - Domain knowledge remains very important in practice