Feature Engineering

- **Most creative aspect of Data Science.**
- Treat like any other creative endeavor, like writing a comedy show:
- Hold brainstorming sessions
- Create templates / formula's
- Check/revisit what worked before

Categorical Features

- Nearly always need some treatment
- High cardinality can create very sparse data
- Difficult to impute missing

Onehot encoding

- **One-of-K encoding on an array of length K.**
- Basic method: Used with most linear algorithms
- Dropping first column avoids collinearity
- Sparse format is memory-friendly
- Most current implementations don't gracefully treat missing, unseen variables

Onehot encoding

```
Sample: ["BR"]

country        country=NL country=BR country=US
-------        ---------- ---------- ----------
NL      => [            0,         1,         0]
BR
US

Encoded dense: [0, 1, 0]
Encoded sparse: 2:1
```

Hash encoding

- **Does "OneHot-encoding" with arrays of a fixed length.**
- Avoids extremely sparse data
- May introduce collisions
- Can repeat with different hash functions and bag result for small bump in accuracy
- Collisions usually degrade results, but may improve it.
- Gracefully deals with new variables (eg: new user-agents)

Hash encoding

```
Sample: ["BR"]

hash("BR") => `2`

country      hash1 hash2 hash3 hash4 hash5
-------      ----- ----- ----- ----- -----
NL      => [     0     1,     0     0,     0]
BR
US

Encoded dense: [0, 1, 0, 0, 0]
Encoded sparse: 2:1
```

Label encoding

- Give every categorical variable a unique numerical ID
- Useful for non-linear tree-based algorithms
- Does not increase dimensionality
- Randomize the cat_var -> num_id mapping and retrain, average, for small bump in accuracy.

Label encoding

```
Sample: ["Queenstown"]

city                city
-----------         ----
Cherbourg              1
Queenstown    =>       2
Southampton            3

Encoded: [2]
```

Count encoding

- Replace categorical variables with their count in the train set
- Useful for both linear and non-linear algorithms
- Can be sensitive to outliers
- May add log-transform, works well with counts
- Replace unseen variables with `1`
- May give collisions: same encoding, different variables

Count encoding

```
Sample: ["A6GHBD78"]

teacher_ID      teacher_ID
----------      ----------
DEADB33F                 4
A6GHBD78                 3
DEADB33F                 4
FCKGWRHQ   =>            1
DEADB33F                 4
A6GHBD78                 3
A6GHBD78                 3
DEADB33F                 4

encoded: [3]
```

LabelCount encoding

- **Rank categorical variables by count in train set**
- Useful for both linear and non-linear algorithms
- Not sensitive to outliers
- Won’t give same encoding to different variables
- Best of both worlds

LabelCount encoding

```
tld       tld
---       ---
nl          3
nl          3
nl          3
nl   =>     3
de          2
de          2
fr          1
fr          1
```

Target encoding

- **Encode categorical variables by their ratio of target (binary classification or regression)**
- Be careful to avoid overfit!
- Form of stacking: single-variable model which outputs average target
- Do in cross-validation manner
- Add smoothing to avoid setting variable encodings to 0.
- Add random noise to combat overfit
- When applied properly: Best encoding for both linear and non-linear

Target encoding

```
role          y       role
---------     -       ----
manager     | 1       0.5
engineer    | 1       0.66
scientist   | 1  =>   1.
manager     | 0       0.5
engineer    | 0       0.66
engineer    | 1       0.66
```

Category Embedding

- **Use a Neural Network to create dense embeddings from categorical variables.**
- Map categorical variables in a function approximation problem into Euclidean spaces
- Faster model training.
- Less memory overhead.
- Can give better accuracy than 1-hot encoded.
- https://arxiv.org/abs/1604.06737

Category Embedding

role	role 3-D embedding
manager	[0.05, 0.10, 0.96]
engineer	[0.72, 0.66, 0.17]
scientist	[0.75, 0.62, 0.15]
manager	[0.05, 0.10, 0.96]
engineer	[0.72, 0.66, 0.17]
engineer	[0.72, 0.66, 0.17]

NaN encoding

- **Give NaN values an explicit encoding instead of ignoring**
- NaN-values can hold information
- Be careful to avoid overfit!
- Use only when NaN-values in train and test set are caused by the same, or when local validation proves it holds signal

NaN encoding

```
Sample = [NaN]

UA           UA=mobile UA=tablet UA=NaN
-------      --------- --------- ------
mobile               0         0      1
tablet
mobile  =>
NaN
mobile

Encoded = [0, 0, 1]
```

Polynomial encoding

- **Encode interactions between categorical variables**
- Linear algorithms without interactions can not solve the XOR problem
- A polynomial kernel *can* solve XOR
- Explodes the feature space: use FS, hashing and/or VW

Polynomial encoding

```
A B   y    A=1*B=1 A=0*B=1 A=1*B=0 A=0*B=0   y
- -   -    ------- ------- ------- -------   -
1 1 | 1          1       0       0       0 | 1
0 1 | 0 =>       0       1       0       0 | 0
1 0 | 0          0       0       1       0 | 0
0 0 | 1          0       0       0       1 | 1
```

Expansion encoding

- **Create multiple categorical variables from a single variable**
- Some high cardinality features, like user-agents, hold far more information in them:
- is_mobile?
- is_latest_version?
- Operation_system
- Browser_build
- Etc.

Expansion encoding

```
Mozilla/5.0 (Macintosh; Intel Mac OS X
10_10_4) AppleWebKit/537.36 (KHTML, like
Gecko) Chrome/53.0.2785.143 Safari/537.36

|
v

UA1    UA2            UA3     UA4 UA5
------ -------------- ------- --- -------
Chrome 53.0.2785.143 Desktop Mac 10_10_4
```

Consolidation encoding

- **Map different categorical variables to the same variable**
- Spelling errors, slightly different job descriptions, full names vs. abbreviations
- Real data is messy, free text especially so

Expansion encoding

```
company_desc                desc1 company_desc2
-----------------           ----- -------------
Shell                       Shell   Gas station
shel                        Shell   Gas station
SHELL                       Shell   Gas station
Shell Gasoline              Shell   Gas station
BP                     =>      BP   Gas station
British Petr.                  BP   Gas station
B&P                            BP   Gas station
BP Gas Station                 BP   Gas station
bp                             BP   Gas station
Procter&Gamble                P&G  Manufacturer
```

Numerical Features

- Can be more readily fed into algorithms
- Can constitute floats, counts, numbers
- Easier to impute missing data

Rounding

- **Round numerical variables**
- Form of lossy compression: retain most significant features of the data.
- Sometimes too much precision is just noise
- Rounded variables can be treated as categorical variables
- Can apply log-transform before rounding

Rounding

```
age                 age1 age2
-------             ---- ----
23.6671               23    2
23.8891               23    2
22.1261    =>         22    2
19.5506               19    1
18.2114               18    1
```

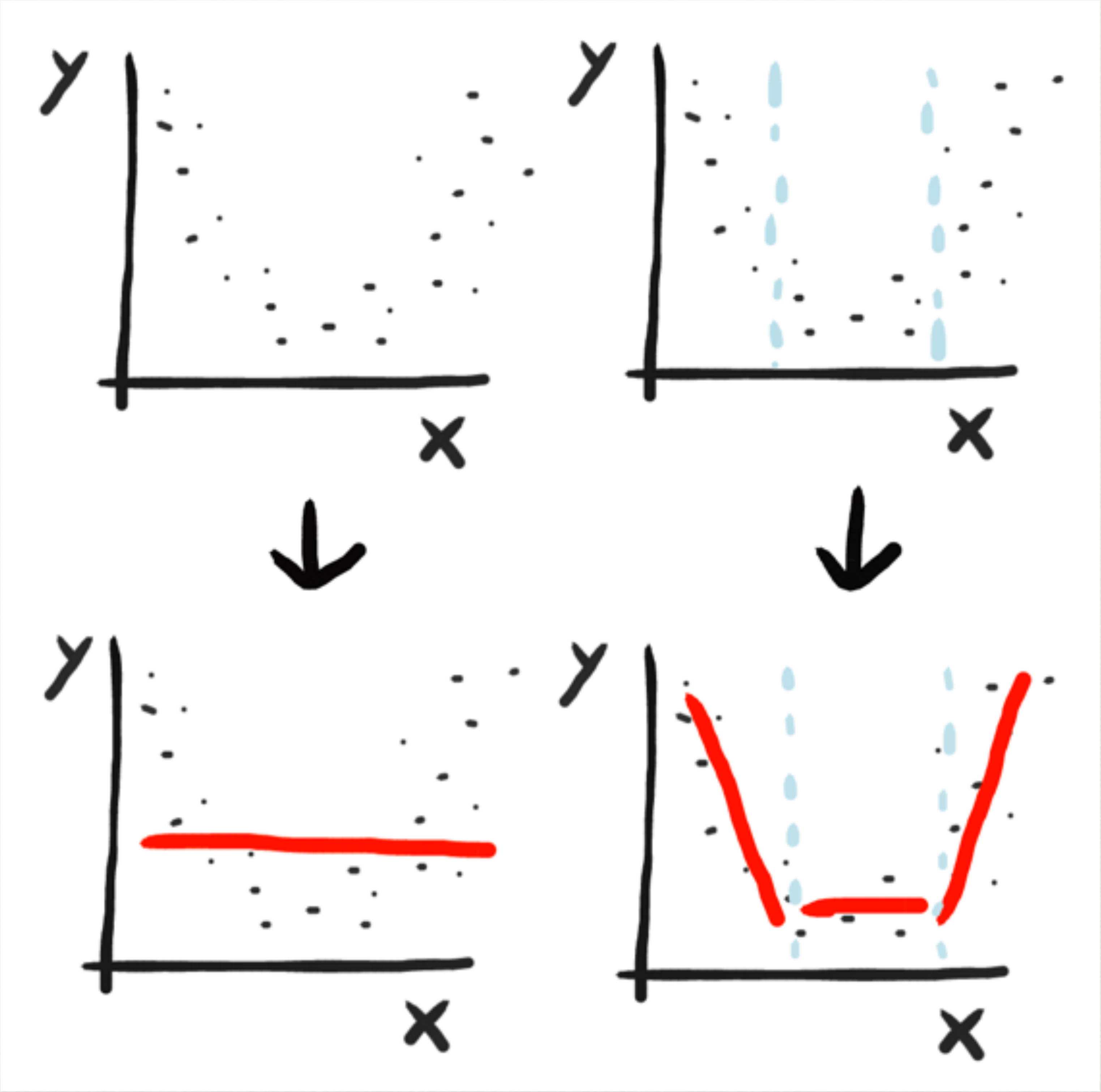
Binning

- **Put numerical variables into a bin and encode with bin-ID**
- Binning can be set pragmatically, by quantiles, evenly, or use models to find optimal bins
- Can work gracefully with variables outside of ranges seen in the train set

Binning

```
risk_score     rs[-inf,33] rs[33,66] rs[66,inf]
----------     ----------- --------- ----------
        15               1         0          0
        77               0         0          1
        78 =>            0         0          1
        55               0         1          0
        42               0         1          0
```

Binning



Scaling

- **Scale to numerical variables into a certain range**
- Standard (Z) Scaling
- MinMax Scaling
- Root scaling
- Log scaling

Imputation

- **Impute missing variables**
- Hardcoding can be combined with imputation
- Mean: Very basic
- Median: More robust to outliers
- Ignoring: just postpones the problem
- Using a model: Can expose algorithmic bias

Imputation

```
wage hours gender | y        wage hours | gender_y
---- ----- ------ | -        ---- ----- | --------
1600 40    0      | 1        1600 40    | 0
2200 50    1      | 1        2200 50    | 1
1800 36    0      | 0   =>   1800 36    | 0
2100 45    1      | 0        2100 45    | ?
2050 60    NaN    | 0        2050 60    | ?
1650 36    0      | 1        1650 36    | ?
```

Interactions

- **Specifically encodes the interactions between numerical variables**
- Try: Substraction, Addition, Multiplication, Divison
- Use: Feature selection by statistical tests, or trained model feature importances
- Ignore: Human intuition; weird interactions can give significant improvement!

Non-linear encoding for linear algo's

- **Hardcode non-linearities to improve linear algorithms**
- Polynomial kernel
- Leafcoding (random forest embeddings)
- Genetic algorithms
- Locally Linear Embedding, Spectral Embedding, t-SNE

Row statistics

- **Create statistics on a row of data**
- Number of NaN’s,
- Number of 0’s
- Number of negative values
- Mean, Max, Min, Skewness, etc.

Temporal Variables

- Temporal variables, like dates, need better local validation schemes (like backtesting)
- Easy to make mistakes here
- Lots of opportunity for major improvements

Projecting to a circle

- **Turn single features, like day_of_week, into two coordinates on a circle**
- Ensures that distance between max and min is the same as min and min +1.
- Use for day_of_week, day_of_month, hour_of_day, etc.

Trendlines

- **Instead of encoding: total spend, encode things like: Spend in last week, spend in last month, spend in last year.**
- Gives a trend to the algorithm: two customers with equal spend, can have wildly different behavior — one customer may be starting to spend more, while the other is starting to decline spending.

Closeness to major events

- **Hardcode categorical features like: date_3_days_before_holidays:1**
- Try: National holidays, major sport events, weekends, first Saturday of month, etc.
- These factors can have major influence on spending behavior.

Spatial Variables

- Spatial variables are variables that encode a location in space
- Examples include: GPS-coordinates, cities, countries, addresses

Categorizing location

- Kriging
- K-means clustering
- Raw latitude longitude
- Convert cities to latitude longitude
- Add zip codes to streetnames

Closeness to hubs

- **Find closeness between a location to a major hub**
- Small towns inherit some of the culture/context of nearby big cities
- Phone location can be mapped to nearby businesses and supermarkets

Spatial fraudulent behavior

- **Location event data can be indicative of suspicious behavior**
- Impossible travel speed: Multiple simultaneous transactions in different countries
- Spending in different town than home or shipping address
- Never spending at the same location

Exploration

- **Data exploration can find data health issues, outliers, noise, feature engineering ideas, feature cleaning ideas.**
- Can use: Console, Notebook, Pandas
- Try simple stats: Min, max
- Incorporate the target so find correlation between signal.

Iteration / Debugging

- **Feature engineering is an iterative process: Make your pipelines suitable for fast iteration.**
- Use sub-linear debugging: Output intermediate information on the process, do spurious logging.
- Use tools that allow for fast experimentation
- More ideas will fail, than ideas will work

Label Engineering

- **Can treat a label/target/dependent variable as a feature of the data and vice versa.**
- Log-transform: y -> log(y+1) | exp(y_pred) - 1
- Square-transform
- Box-Cox transform
- Create a score, to turn binary target in regression.
- Train regressor to predict a feature not available in test set.

Natural Language Processing

- Can use the same ideas from categorical features.
- Deep learning (automatic feature engineering) increasingly eating this field, but shallow learning with well-engineered features is still competitive.
- High sparsity in data introduces you to “curse of dimensionality”
- Many opportunities for feature engineering:

Natural Language Processing

- Lowercasing,
- Removing non-alphanumeric,
- Repairing,
- Encoding punctuation marks,
- Tokenizing,
- Token-grams,
- skipgrams,
- char-grams,
- Removing stopwords,
- Removing rare words
- and very common words,
- Spelling Correction,
- Chopping,
- Stemming,
- Lemmatization,
- Document features,
- Entitity Insertion & Extraction
- Simplification,
- Word2Vec and GloVe / Doc2Vec,
- String Similarity,
- Reading level,
- Nearest Neighbors,
- TF*IDF,
- BayesSVM, Vectorization, LDA, LSA.

Cleaning

- **Lowercasing**: Make tokens independant of capitalisation: “I work at NASA” -> “i work at nasa”.
- **Unidecode**: Convert accented characters to their ascii-counterparts: “Memórias Póstumas de Brás Cubas” -> “Memorias Postumas de Bras Cubas”
- **Removing non-alphanumeric**: Clean text by removing anything not in [a-z] [A-Z] [0-9]. “Breaking! Amsterdam (2009)” -> “Breaking Amsterdam 2009”
- **Repairing**: Fix encoding issues or trim intertoken spaces. “C a s a C a f é” -> “Casa Café”

Tokenizing

- **Encode punctuation marks**: Hardcode "!" and "?" as tokens.
- **Tokenize**: Chop sentences up in word tokens.
- **N-Grams**: Encode consecutive tokens as tokens: "I like the Beatles" -> ["I like", "like the", "the Beatles"]
- **Skip-grams**: Encode consecutive tokens, but skip a few: "I like the Beatles" -> ["I the", "like Beatles"]
- **Char-grams**: Same as N-grams, but character level: "Beatles" -> ["Bea", "eat", "atl", "tle", "les"]
- **Affixes**: Same as char-grams, but only the postfixes and prefixes

Removing

- **Stopwords**: Remove words/tokens that appear in stopword lists.
- **Rare words**: Remove words that only appear few times in training set.
- **Common words**: Remove extremely common words that may not be in a stopword list.

Roots

- **Spelling correction**: Change tokens to their correct spelling.
- **Chop**: Take only the first n (8) characters of a word.
- **Stem**: Reduce a word/token to its root. “cars” -> “car”
- **Lemmatize**: Find semantic root “never be late” -> “never are late”

Enrich

- **Document features**: Count number of spaces, tabs, newlines, characters, tokens, etc.
- **Entity insertion**: Add more general specifications to text “Microsoft releases Windows” -> “Microsoft (company) releases Windows (application)”
- **Parse Trees**: Parse a sentence into logic form: “Alice hits Bill” -> Alice/Noun_subject hits/Verb Bill/Noun_object.
- **Reading level**: Compute the reading level of a document.

Similarities

- **Token similarity**: Count number of tokens that appear in two texts.
- **Compression distance**: Look if one text can be compressed better using another text.
- **Levenshtein/Hamming/Jaccard Distance**: Check similarity between two strings, by looking at number of operations needed to transform one in the other.
- **Word2Vec / Glove**: Check cosine similarity between two averaged vectors.

TF-IDF

- **Term Frequency**: Reduces bias to long documents.
- **Inverse Document Frequency**: Reduces bias to common tokens.
- **TF-IDF:** Use to identify most important tokens in a document, to remove unimportant tokens, or as a preprocessing step to dimensionality reduction.

Dimensionality Reduction

- **PCA**: Reduce text to 50 or 100-dimensional vector.
- **SVD**: Reduce text to 50 or 100-dimensional vector.
- **LDA**: TF-IDF followed by SVD.
- **LSA**: Create topic vectors.

External models

- **Sentiment Analyzers**: Get a vector for negative or positive sentiment for any text.
- **Topic models:** Use another dataset to create topic vectors for a new dataset.

Neural Networks & Deep Learning

- **Neural networks claim end-to-end automatic feature engineering.**
- Feature engineering dying field?
- No! Moves the focus to architecture engineering
- And despite promise: computer vision uses features like: HOG, SIFT, whitening, perturbation, image pyramids, rotation, z-scaling, log-scaling, frame-grams, external semantic data, etc.

Leakage / Golden Features

- **Feature engineering can help exploit leakage.**
- Reverse engineer:
  - Reverse MD5 hash with rainbow tables.
  - Reverse TF-IDF back to Term Frequency
  - Encode order of samples data set.
  - Encode file creation dates.
- Rule mining:
  - Find simple rules (and encode these) to help your model.

Resources & Further Reading

- **Kaggle forums & kernels:** Far0n, KazAnova, Fchollet, Abhishek, Gilberto Titericz, Leustagos, Owen Zhang, Gert Jacobusse …
- **Introduction:** http://machinelearningmastery.com/discover-feature-engineering-how-to-engineer-features-and-how-to-get-good-at-it/
- **Books:**
  - Mastering Feature Engineering (Alice Zheng),
  - Feature Extraction (Isabelle Guyon et al.)
- **Blogs**:
  - https://smerity.com/articles/2016/architectures_are_the_new_feature_engineering.html
  - http://hunch.net/~jl/projects/hash_reps/
  - https://blogs.technet.microsoft.com/machinelearning/2014/09/24/online-learning-and-sub-linear-debugging/
  - http://blog.kaggle.com/2015/12/03/dato-winners-interview-1st-place-mad-professors/
  - http://blog.kaggle.com/2016/08/24/avito-duplicate-ads-detection-winners-interview-1st-place-team-devil-team-stanislav-dmitrii/
  - http://www.slideshare.net/DataRobot/featurizing-log-data-before-xgboost
- **Data:** https://data.quora.com/First-Quora-Dataset-Release-Question-Pairs
- **Software:** https://github.com/trevorstephens/gplearn