PUT DOWN THE DEEP LEARNING When not to use neural networks (and what to do instead)

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Additionally, for $\mathsf{BERT}_{\mathsf{LARGE}}$ we found that fine-tuning was sometimes unstable on small data sets (i.e., some runs would produce degenerate results), so we ran several random restarts and selected the model that performed best on the Dev set. (Devlin et al 2019)



Follow

V

@quasimondo

How much would it cost to train your own #BigGAN from scratch if we had the training code?

The 512x512 model requires 512 TPU v3 which cost US\$ 2.40 per TPU per hour. According to the paper it takes between 24 and 48 hours to train a model.





I would personally use deep learning if...

- A human can do the same task extremely quickly (<1 second)
- I have high tolerance for weird errors
- I don't need to explain myself
- I have a large quantity of labelled data (>5,000 items per class)
- I've got a lot of time (for training) and money (for annotation and compute)



4:45 PM - 7 Mar 2016



| Method | Time | Money | Data |
|------------------|-------|-------|-----------|
| Deep Learning | A lot | A lot | A lot |
| | | | |
| | | | |
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| Method | Time | Money | Data |
|-------------------|-------|-------|-----------|
| Deep Learning | A lot | A lot | A lot |
| Regression | | | |
| Trees | | | |
| Distance Based | | | @rctatman |

Regression





The OG ML technique

- In regression, you pick the family of the function you'll use to model your data
- Many existing kinds of regression models
- ✓ Fast to fit
- ✓ Works well with small data
- Easy to interpret
- × More data preparation
- Models require validation



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My go-to? Mixed effects regression





imports for mixed effect libraries
import statsmodels.api as sm
import statsmodels.formula.api as smf

```
# fit model
fitted_model = md.fit()
```



Mixed Linear Model Regression Results

| Model: No. Observation No. Groups: Min. group size Max. group size Mean group size | ons: 300 5 ze: 21 ze: 99 | Scale Likel Conve | d: | | chance_of REML 0.0055 332.7188 Yes | ===== _admit |
|---|-----------------------------------|----------------------------------|---------------------------|-------------------------|--|--------------------------|
| | | Std.Err. | Z | P> z | [0.025 | 0.975] |
| Intercept gre_score toefl_score Group Var | -1.703 0.005 0.007 0.002 | 0.169 0.001 0.001 0.020 | -10.097 7.797 4.810 | 0.000 0.000 0.000 | 0.004 | -1.372 0.007 0.009 |



| Method | Time | Money | Data |
|-------------------|-------|----------|-----------|
| Deep Learning | A lot | A lot | A lot |
| Regression | Some | A little | A little |
| Trees | | | |
| Distance Based | | | @rctatman |





Tree based methods



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Random Forests

- An **ensemble** model that combines many trees into a single model
- Very popular, especially with Kaggle competitors
 - 63% of Kaggle Winners
 (2010-2016) used random forests,
 only 43% deep learning
- Tend to have better performance than logistic regression
 - "<u>Random forest versus logistic</u> regression: a large-scale benchmark <u>experiment</u>", Couronné et al 2018



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Benefits & Drawbacks

- Require less data cleaning & model validation
- Many easy to use packages
 - XGBoost, LightGBM, CatBoost, new one in next scikit-learn release candidate
 - Can overfit
 - Generally more sensitive to differences between datasets
 - Less interpretable than regression Especially for ensembles, can require more compute/training time





import xgboost as xgb

split training data into inputs & outputs
X = train.drop(["chance_of_admit"], axis=1)
Y = train["chance_of_admit"]

specify model (xgboost defaults are generally fine)
model = xgb.XGBRegressor()

fit our model
model.fit(y=Y, X=X)



| Method | Time | Money | Data |
|-------------------|---------------------------------|----------|-----------|
| Deep Learning | A lot | A lot | A lot |
| Regression | Some | A little | A little |
| Trees | Some (esp for big ensembles) | A little | Some |
| Distance Based | | | @rctatman |







Distance based methods

- Basic idea: points closer together to each other in feature space are more likely to be in the same group
- Some examples:
 - K-nearest neighbors
 - Gaussian Mixture Models
 - Support Vector Machines



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Benefits & Drawbacks

- Work well with small datasets
 Tend to be *very* fast to train
 Overall accuracy is fine, other methods usually better
 Good at classification, generally crummy/slow at estimation
 These days, tend to show up
 - mostly in ensembles
 - Can be a good fast first pass at a problem





from sklearn.svm import SVR

split training data into inputs & outputs

- X = train.drop(["chance_of_admit"], axis=1)
- Y = train["chance_of_admit"]

specify hyperparameters for regression model
model = SVR(gamma='scale', C=1.0, epsilon=0.2)

fit our model
model.fit(y=Y, X=X)



| Method | Time | Money | Data |
|-------------------|---------------------------------|-------------|-------------|
| Deep Learning | A lot | A lot | A lot |
| Regression | Some | A little | A little |
| Trees | Some (esp for big ensembles) | A little | Some |
| Distance Based | Very little | Very little | Very little |

So what method should you use?



| Method | Time | Money | Data |
|-------------------|---------------------------------|-------------|-------------|
| Deep Learning | A lot | A lot | A lot |
| Regression | Some | A little | A little |
| Trees | Some (esp for big ensembles) | A little | Some |
| Distance Based | Very little | Very little | Very little |

| Method | Time | Money | Data | Performance (Ideal case) |
|-------------------|-------------|-------------|-------------|-----------------------------|
| Deep Learning | A lot | A lot | A lot | Very high |
| Regression | Some | A little | A little | Medium |
| Trees | Some | A little | Some | High |
| Distance Based | Very little | Very little | Very little | So-so |



Data Science != Deep Learning

- Deep learning is extremely powerful but it's not for everything
- Don't be a person with a hammer
- Deep learning isn't the core skill in professional data science
 - "I always find it interesting how little demand there is for DL skills... Out of >400 postings so far, there are 5 containing either PyTorch, TensorFlow, Deep Learning or Keras" -- Dan Becker





Thanks! Questions?

Code & Slides:

http://www.kaggle.com/rtatman/non-deep-learning-approaches http://www.rctatman.com/talks/



Honorable mention: Plain ol' rules





Some examples of proposed deep learning projects from the Kaggle forums that should probably be rule-based systems:

- Convert Roman numerals (IX, VII) to Hindu-Arabic numerals (9, 7)
- Automate clicking the same three buttons in a GUI in the same order
- Given a graph, figure out if a list of nodes is a valid path through it
- Correctly parse dates from text (e.g. "tomorrow", "today")

Remember: If it's stupid but it works, it's not stupid.



