U D A C I T Y

PROJECT

Finding Donors for CharityML

A part of the Machine Learning Engineer Nanodegree Program

PROJECT REVIEW

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SHARE YOUR ACCOMPLISHMENT!

Meets Specifications

Dear student,

This is awesome work. You have done a terrific job on this! I am very impressed.

Please see my comments and notes.
Please also let me know if you've found my review helpful or not. I am always interested to improve my reviews, so please let me know how I did for you.
I directly receive your feedback from your star rating and comments about the review

thanks
-Gilad

Exploring the Data

Student's implementation correctly calculates the following:

- Number of records
- Number of individuals with income >$50,000
- Number of individuals with income <=$50,000
- Percentage of individuals with income > $50,000

Preparing the Data

Student correctly implements one-hot encoding for the feature and income data.

Evaluating Model Performance

Student correctly calculates the benchmark score of the naive predictor for both accuracy and F1 scores.

The pros and cons or application for each model is provided with reasonable justification why each model was chosen to be explored.

Please list all the references you use while listing out your pros and cons.

This is a good discussion, you go into each algorithm and demonstrate a good understanding of what assumptions they are making, what pro's and con's exist.

Some tips for writing up summaries of algorithms

Don't editorialize:

ADJECTIVES IMPLY OPINIONS

- very fast
- highly susceptible
- very simple
- performs poorly
- performs very well
- when the data is large (large is a relative term, what *is* large actually? 100? 1000? 1 million?)
- when the data is small (see above)

These are all essentially opinions of the writer. They aren't substantiated as facts, they are just what someone believes or thinks.

Instead it's much better to write with quantitative and objective prose.

Quantitative writing

PRESENT ONLY THE *FACTS*

- the algorithm increases with exponential time
- is able to capture non linear boundaries
- is restricted to linear separations
- makes the assumption that the underlying data is normally distributed
- if the data is > 300k samples ...
- if the data is < 1000 samples ....

When we write objectively without adjectives, we let the reader make their *own* conclusions about the algorithms (or our research). This also causes the reader to trust your expertise much more, because they aren't being asked to simply believe what you are saying. The reader will think for themselves, and draw their own conclusions. Instead of deciding whether or not they believe your narrative, they will be grateful for the information you have provided them. It shifts the focus from "do I trust this writer?" to "this writer has given me useful information" and "this writer is knowledgable about the subject"

These tips will aid all your writing.

Student successfully implements a pipeline in code that will train and predict on the supervised learning algorithm given.

Student correctly implements three supervised learning models and produces a performance visualization.

A note on random states

The `random_state` parameter of many algorithms (classifiers / models) in sklearn are used to "fix" your model, so it can be reproduced over and over. Sometimes models or methods, require an element of randomness. For example shuffling and splitting the data is required to be random. However, since the results change ever so slightly each time you re-run the method -- it can be frustrating (scores will change slightly). For this reason Udacity has in the past required students to set the `random_state` variable in the methods.

By assigning a `random_state = 1` variable in the argument to the method -- we *actually remove all randomness* from the method. In essence, the algorithm becomes deterministic (fixed) and the results will always be the same.

I get it for "double checking" someone elses implementation. But I don't like them in general.
Why?
Because it creates a slice of the model, which isn't representative of the real model. The real model has randomized parameters, so it should randomly change every time you instantiate it. This means that typically to get real results, you need to run the model multiple time (hundreds) in order to know *in general* how it will perform.
When the difference between two models is <1%, can we be sure one model is better than the other? Especially when we've randomly created a static version of that model by freezing it's random variables? It's not really possible. So I would advise that the better solution would be to run the experiment (with randomness) a few hundred times and then average the results. This would be a much better indicator of what kind of performance you can get.
ShuffleSplit is a great method to do this kind of experiment.

Keep in mind I offer this as advice for your future work, using a random_state here is absolutely fine, but I always like to teach best practices when I can offer them, and I believe this to be one.

Improving Results

Justification is provided for which model appears to be the best to use given computational cost, model performance, and the characteristics of the data.

I agree with you here entirely. At the end of the day most often, we simply want the highest performing algorithm in terms of the error metric. This is why it's so critical to choose an error metric that accurately represents the problem which you are trying to solve. In this notebook we've chosen f-beta with the value 0.5, and the best algorithm should be the one that does best on that metric.
Training and prediction times are often minor considerations. There are cases where this matters (real-time scenarios, but in my experience it's not the general case). So for this

problem, since we probably only need to make predictions once in a while (maybe once a day) and can train separately (to update with new data), I wouldn't worry about training or prediction times.

The requirement of the company in this case is mailing out letters. It's not a real-time scenario. It's certainly going to be done on a regularly scheduled time-frame. Even if we had to train for 2 hours or 2 days, I'd prefer to train as long as needed in order to get the best possible results from our model.

As a note, since you chose to explore extra models (nice work here!), you may be interested in this post about the SGD classifier.
https://discussions.udacity.com/t/sgdclassifier-is-not-a-unique-model/341776

Student is able to clearly and concisely describe how the optimal model works in layman's terms to someone who is not familiar with machine learning nor has a technical background.

Your explanation is clear and concise, I can follow it quite well. I'm not 100% sure "laymen" would understand it, because you've used a lot of ML terms here. If you were truly going to present to non data science folks, I'd try to get even higher level.
Still that's quite a challenging task, and I don't really think many of us are capable of it.

I'm always tempted to show my boss this comic when asked what my model does.

The final model chosen is correctly tuned using grid search with at least one parameter using at least three settings. If the model does not need any parameter tuning it is explicitly stated with reasonable justification.

Great job checking parameters. Often times we may feel this part of the work is tiresome, but by fine tuning the parameters to fit the data better, we can boost performance considerably.

Awesome that you did it on more than one model. This attitude is what makes people excellent ML engineers, the need to *know* how models will work.

Also note you can get the final parameters of the model from gridsearchCV by accessing it's `best_params_` attribute.
see the docs here
http://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html

You may want to try out randomized search:
http://scikit-learn.org/stable/modules/generated/sklearn.model_selection.RandomizedSearchCV.html
This blog does a good job introducing the idea and giving intuitions for why it works quite well in practice.

Student reports the accuracy and F1 score of the optimized, unoptimized, models correctly in the table provided. Student compares the final model results to previous results obtained.

Feature Importance

Student ranks five features which they believe to be the most relevant for predicting an individual's' income. Discussion is provided for why these features were chosen.

Nice discussion. It's actually quite hard to know what will be important. Your thought process is lucid and clear.

Student correctly implements a supervised learning model that makes use of the `feature_importances_` attribute. Additionally, student discusses the differences or similarities between the features they considered relevant and the reported relevant features.

Keep in mind that the original categorical features got OHE, so it's possible their "power" was diluted somewhat.
Either way it's always interesting to do this analysis especially if we consider gathering more data.

You can also do feature selection on the non-OHE features quite easily with many different methods.
http://scikit-learn.org/stable/modules/feature_selection.html

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Student analyzes the final model's performance when only the top 5 features are used and compares this performance to the optimized model from Question 5.

Your discussion here is great.
I would just add that sometimes though we may even see an increase in our classifiers performance by dropped features which aren't important. This is due to the curse of dimensionality -- our models may perform better if the dimensionality of the data gets reduced.
So it's good to check.

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▶ visuals.py

▶ finding_donors_MD_Alamgir.html

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Review #1 (this review)

Reviewed 11h ago

STUDENT NOTES

Please see the following files in the repository:
finding_donors_MD_Alamgir.html
finding_donors_MD_Alamgir.ipynb
visuals.py
To be comprehensive, two sets of three classifierseach have been evaluated for predicting the CharityML income. All questions in the Jupyter notebook have been answered per guidelines provided.
Adaboost is the final model selected and charityML dataset is analyzed and the model optimized (parameter-tuned). The model accuracy (0.8676) and f-score (0.7448) for the AdaBoost model are reasonably good.

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