Notebook

December 29, 2019

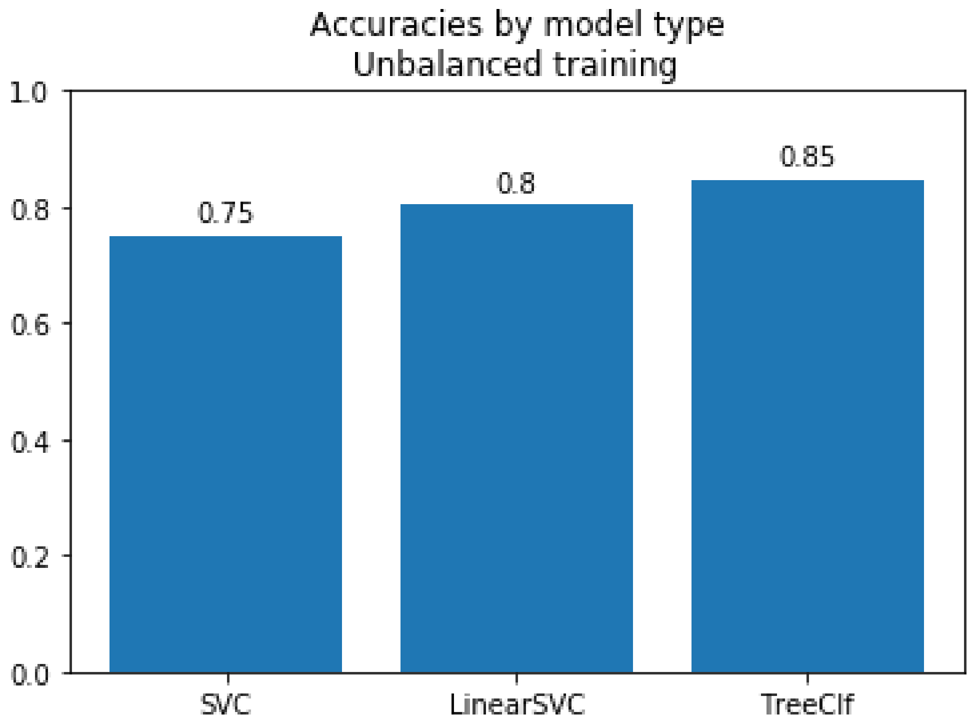
```
In [8]: import pandas as pd
        import numpy as np
        import json
        import matplotlib.pyplot as plt
        from util import resultsmngr, analyzer
```

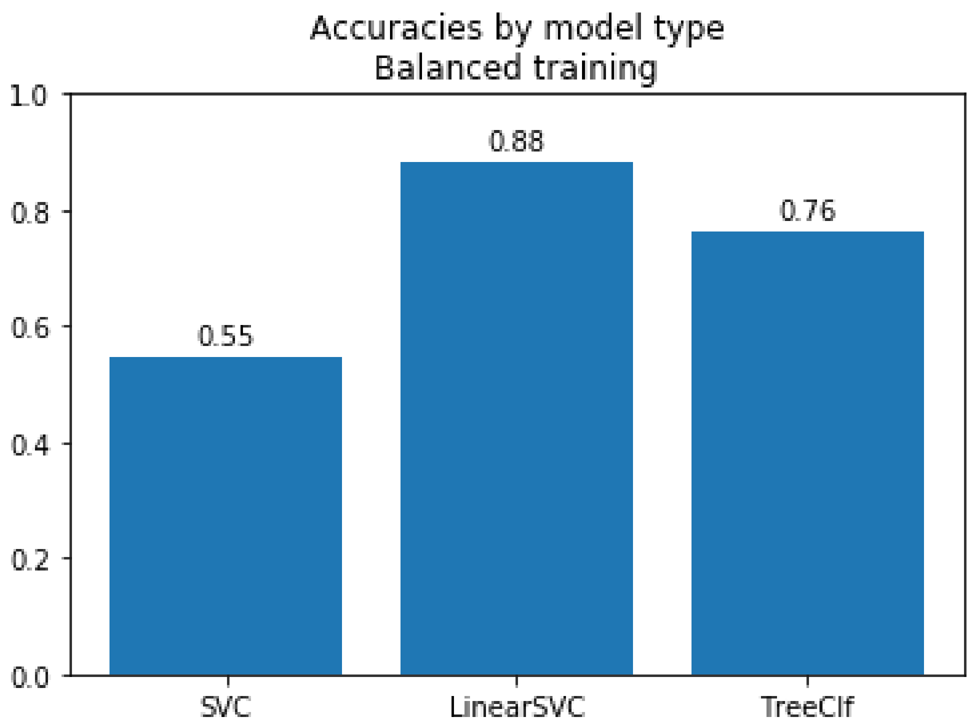
```
In [9]: unbalanced_results = resultsmngr.load('CensusIncome/results/1577576647.json')
        balanced_results = resultsmngr.load('CensusIncome/results/1577579934.json')

        def graphBestByModelType(results, **kw):
          best = analyzer.bestparams(results)
          fig, ax = plt.subplots()
          ax.set_ylim((0, 1))
          rex = ax.bar(range(len(best)), [best[b]['metrics']['testing-accuracy'] for b in best]
          ax.set_xticks(range(len(best)))
          ax.set_xticklabels(list(best))
          for r in rex:
            ht = r.get_height()
            ax.annotate(
              str(round(ht, 2)),
              xy=(r.get_x() + r.get_width() / 2, ht),
              xytext=(0, 3),  # 3 points vertical offset
              textcoords="offset points",
              ha='center', va='bottom')
          ax.set_title(kw.get('title', 'Accuracies'))
          return best
```

0.1 Look at best performance for each model type

```
In [10]: unb_best = graphBestByModelType(unbalanced_results, title="Accuracies by model type\nU
         b_best = graphBestByModelType(balanced_results, title="Accuracies by model type\nBalan
```


Accuracies by model type
Unbalanced training
1.0
0.8
0.6
0.4
0.2
0.0
0.75
0.8
0.85
SVC
LinearSVC
TreeClf


Accuracies by model type
Balanced training
1.0
0.8
0.6
0.4
0.2
0.0
0.55
0.88
0.76
SVC
LinearSVC
TreeClf

0.2 It makes sense to do worse in a balanced setting, since we aren't being lazy and always guessing the predominant class. I'm going to stick with the model that performed best in the balanced setting since it is more general and "real world"

```
In [11]: print(json.dumps(b_best['LinearSVC'], indent=4))
```


```
{
    "params": null,
    "metrics": {
        "training-accuracy": 0.6142781033564199,
        "testing-accuracy": 0.8806878306878307
    }
}
```


0.3 Seems like a LinearSVC will be best so lets GridSearch on a wide range of params

```
In [13]: from util import preprocessor, splitfuncs, metrics
         from sklearn.model_selection import GridSearchCV
         from sklearn.svm import LinearSVC

         # setup model and params to test
         model = LinearSVC()
         parameters = {
           'loss': ['hinge', 'squared_hinge'],
           'C': np.linspace(0.1, 5, 5)
         }

         # get data and train/test splits
         pre = preprocessor()
         trx, try_ = pre.data
         # this is optional but lets me CV on balanced sets
         splits = []
         for i in range(5):
           tri, i, tei, j = splitfuncs.splitBalanced(trx, try_)
           splits.append((tri.index, tei.index))

         # get our best params and retrain a new model
         clf = GridSearchCV(model, parameters, cv=splits)
         gs = clf.fit(trx, try_)
         model = LinearSVC(**gs.best_params_)

         # check model performance
         trx, try_, tex, tey = splitfuncs.splitBalanced(trx, try_)
         model.fit(trx, try_)
         preds = model.predict(tex)
         acc = metrics.acc(preds, tey)
```

```python
        print("Best params: ", gs.best_params_)
        print("Accuracy:    ", acc)
```

```
Best params:  {'C': 0.1, 'loss': 'squared_hinge'}
Accuracy:     0.9004761904761904
```

0.4 So that didn't get us very far, but good to know we're doing the best we can