Evaluating Themis-ml

September 5, 2017

1 The Utility-Fairness Tradeoff

In this post, I'll be taking a dive into the capabilities of `themis_ml` as a tool to measure and mitigate discriminatory patterns in training data and the predictions made by machine learning algorithms trained for the purposes of socially sensitive decision processes.

The overall goal of this research is to come up with a reasonable way to think about how to make machine learning algorithms more fair. While the mathematical formalization of fairness is not sufficient to solve the problem of discrimination, our ability to understand and articulate what it means for an algorithm to be fair is a step in the right direction.

Since the "discrimination" is an value-laden term in this context, I'll refer to the opposite of fairness as *potential discrimination* (PD) since the any socially biased patterns we'll be measuring in the training data did not necessarily arise from discriminatory processes.

I'll be using the German Credit data, which consists of ~1000 loan application containing roughly 20 input variables (including `foreign_worker`, `housing`, and `credit_history`) and 1 binary target variable `credit_risk`, which is either `good` or `bad`.

In the context of a `good/bad credit_risk` binary predict task and an explicit definition of fairness, our objectives will be to:

1. Measure the degree of discrimination in the dataset with respect to some discrimination metric and protected class.
2. Establish a baseline performance level with respect to utility and fairness metrics with models trained on a fairness-unaware machine learning pipeline.
3. Measure and compare the baseline metrics with fairness aware models.

2 Load Data

In [2]:
```
from themis_ml import datasets
from themis_ml.datasets.german_credit_data_map import \
    preprocess_german_credit_data
from themis_ml.metrics import mean_difference, normalized_mean_difference
```

In [3]:
```
german_credit = datasets.german_credit()
german_credit[
    ["credit_risk", "purpose", "age_in_years", "foreign_worker"]].head()
```

Out[3]:
```
   credit_risk            purpose  age_in_years  foreign_worker
0            1   radio/television            67               1
```

```
1             0     radio/television            22                1
2             1            education            49                1
3             1  furniture/equipment            45                1
4             0            car_(new)            53                1
```

```
In [4]: german_credit_preprocessed = (
            preprocess_german_credit_data(german_credit)
            # the following binary variable indicates whether someone is female or
            # not since the unique values in `personal_status` are:
            # 'personal_status_and_sex_female_divorced/separated/married'
            # 'personal_status_and_sex_male_divorced/separated'
            # 'personal_status_and_sex_male_married/widowed'
            # 'personal_status_and_sex_male_single'
            .assign(female=lambda df:
                    df["personal_status_and_sex_female_divorced/separated/married"])
            # we're going to hypothesize here that young people, aged below 25,
            # might be  considered to have bad credit risk moreso than other groups
            .assign(age_below_25=lambda df: df["age_in_years"] <= 25)
        )
```

3 Measure Social Bias

3.1 target variable: `credit_risk`

- `1 = low risk` (good)
- `0 = high risk` (bad)

```
In [5]: credit_risk = german_credit_preprocessed.credit_risk
        credit_risk.value_counts()

Out[5]: 1    700
        0    300
        Name: credit_risk, dtype: int64
```

3.2 protected class: sex

- advantaged group: `men`
- disadvantaged group: `women`

```
In [6]: is_female = german_credit_preprocessed.female
        is_female.value_counts()

Out[6]: 0    690
        1    310
        Name: female, dtype: int64
```

```
In [7]: def report_metric(metric, mean_diff, lower, upper):
            print("{metric}: {md:0.04f} - 95% CI [{lower:0.04f}, {upper:0.04f}]"
                  .format(metric=metric, md=mean_diff, lower=lower, upper=upper))
```

```
report_metric("mean difference", *mean_difference(credit_risk, is_female))
report_metric("normalized mean difference",
              *normalized_mean_difference(credit_risk, is_female))
```

```
mean difference: 0.0748 - 95% CI [0.0135, 0.1361]
normalized mean difference: 0.0773 - 95% CI [0.0139, 0.1406]
```

3.3 protected class: immigration status

- advantaged group: `citizen worker`
- disadvantaged group: `foreign worker`

In [8]:
```
is_foreign = german_credit_preprocessed.foreign_worker
is_foreign.value_counts()
```

Out[8]:
```
1    963
0     37
Name: foreign_worker, dtype: int64
```

In [9]:
```
report_metric("mean difference", *mean_difference(credit_risk, is_foreign))
report_metric("normalized mean difference",
              *normalized_mean_difference(credit_risk, is_foreign))
```

```
mean difference: 0.1993 - 95% CI [0.0491, 0.3494]
normalized mean difference: 0.6396 - 95% CI [0.1576, 1.1217]
```

3.4 protected class: age

- advantaged group: `age above 25`
- disadvantaged group: `age below 25`

In [10]:
```
age_below_25 = german_credit_preprocessed.age_below_25
age_below_25.value_counts()
```

Out[10]:
```
False    810
True     190
Name: age_below_25, dtype: int64
```

In [11]:
```
report_metric("mean difference",
              *mean_difference(credit_risk, age_below_25))
report_metric("normalized mean difference",
              *normalized_mean_difference(credit_risk, age_below_25))
```

```
mean difference: 0.1494 - 95% CI [0.0776, 0.2213]
normalized mean difference: 0.1729 - 95% CI [0.0897, 0.2561]
```

These mean differences and confidence interval bounds suggest that on average:

- **men** have "good" credit risk at a *7.48% higher rate* than **women**, with a *lower bound of 1.35%* and *upper bound of 13.61%*.
- **citizen workers** have "good" credit risk at a *19.93%* higher rate than **foreign workers**, with a *lower bound of 4.91%* and *upper bound of 34.94%*.
- **people above the age of 25** have "good" credit risk at a *14.94% higher rate* than those below 25 with a *lower bound of 8.97%* and *upper bound of 25.61%*.

4 Establish Baseline Metrics

Suppose that `Unjust Bank` wants to use these data to train a machine learning algorithm to classify new observations into the "good credit risk"/"bad credit risk" buckets.

In scenario 1, let's also suppose that the data scientists at `Unjust Bank` are using typical, fairness-unaware modeling techniques. Furthermore, they give absolutely no thought into what inputs go into the learning process. Using this kitchen sink approach, they plan on using variables like `sex`, `age_below_25`, and `foreign_worker` to learn the classifier.

However, a rogue element in the data science team is interested in at least measuring the potentially discriminatory (PD) patterns in the learned algorithms, so in addition to measure performance with metrics like `accuracy` or `ROC area under the curve`, also measures the degree to which the algorithm generates PD predictions that favor one social group over another.

Procedure

1. Specify model hyperparameter settings for training models.
2. Partition the training data into 10 validation folds.
3. For each of the validation folds, train model on the rest of the data on each of the hyperparameter settings.
4. Evaluate the performance of the model on the validation fold.
5. Pick model with the best average performance to deploy to production.

Below we use `StratifiedKFold` so that we can partition our data according to the protected class of interest and train the the following models:

- LogisticRegression
- DecisionTreeClassifier
- RandomForest

```
In [12]: import itertools
         import numpy as np
         import pandas as pd

         from sklearn.model_selection import StratifiedKFold
         from sklearn.linear_model import LogisticRegression
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.neural_network import MLPClassifier

         from sklearn.metrics import (
             accuracy_score, roc_auc_score, f1_score)
```

In [13]:
```python
# specify feature set. Note that we're excluding the `is_female`
# and `age_below_25` columns that we created above.
feature_set_1 = [
    'duration_in_month',
    'credit_amount',
    'installment_rate_in_percentage_of_disposable_income',
    'present_residence_since',
    'age_in_years',
    'number_of_existing_credits_at_this_bank',
    'number_of_people_being_liable_to_provide_maintenance_for',
    'status_of_existing_checking_account',
    'savings_account/bonds',
    'present_employment_since',
    'job',
    'telephone',
    'foreign_worker',
    'credit_history_all_credits_at_this_bank_paid_back_duly',
    'credit_history_critical_account/other_credits_existing_not_at_this_bank',
    'credit_history_delay_in_paying_off_in_the_past',
    'credit_history_existing_credits_paid_back_duly_till_now',
    'credit_history_no_credits_taken/all_credits_paid_back_duly',
    'purpose_business',
    'purpose_car_(new)',
    'purpose_car_(used)',
    'purpose_domestic_appliances',
    'purpose_education',
    'purpose_furniture/equipment',
    'purpose_others',
    'purpose_radio/television',
    'purpose_repairs',
    'purpose_retraining',
    'personal_status_and_sex_female_divorced/separated/married',
    'personal_status_and_sex_male_divorced/separated',
    'personal_status_and_sex_male_married/widowed',
    'personal_status_and_sex_male_single',
    'other_debtors/guarantors_co-applicant',
    'other_debtors/guarantors_guarantor',
    'other_debtors/guarantors_none',
    'property_building_society_savings_agreement/life_insurance',
    'property_car_or_other',
    'property_real_estate',
    'property_unknown/no_property',
    'other_installment_plans_bank',
    'other_installment_plans_none',
    'other_installment_plans_stores',
    'housing_for free',
    'housing_own',
    'housing_rent',
```

```
        ]

In [14]: N_SPLITS = 10
         RANDOM_STATE = 1000

         def get_estimator_name(e):
             return "".join([x for x in str(type(e)).split(".")[-1]
                             if x.isalpha()])


         def get_grid_params(grid_params_dict):
             """Get outer product of grid search parameters."""
             return [
                 dict(params) for params in itertools.product(
                     *[[(k, v_i) for v_i in v] for
                       k, v in grid_params_dict.items()])]


         def fit_with_s(estimator):
             has_relabeller = getattr(estimator, "relabeller", None) is not None
             child_estimator = getattr(estimator, "estimator", None)
             estimator_fit_with_s = getattr(estimator, "S_ON_FIT", False)
             child_estimator_fit_with_s = getattr(child_estimator, "S_ON_FIT", False)
             return has_relabeller or estimator_fit_with_s or\
                 child_estimator_fit_with_s


         def predict_with_s(estimator):
             estimator_pred_with_s = getattr(estimator, "S_ON_PREDICT", False)
             child_estimator = getattr(estimator, "estimator", None)
             return estimator_pred_with_s or \
                 getattr(child_estimator, "S_ON_PREDICT", False)

         def cross_validation_experiment(estimators, X, y, s, s_name, verbose=True):
             msg = "Training models: protected_class = %s" % s_name
             if verbose:
                 print(msg)
                 print("-" * len(msg))
             performance_scores = []
             # stratified groups tries to balance out y and s
             groups = [i + j for i, j in
                       zip(y.astype(str), s_female.astype(str))]
             cv = StratifiedKFold(
                 n_splits=N_SPLITS, shuffle=False, random_state=RANDOM_STATE)
             for e_name, e in estimators:
                 if verbose:
                     print("%s, fold:" % e_name),
                 for i, (train, test) in enumerate(cv.split(X, y, groups=groups)):
```

```
        if verbose:
            print(i),
        # create train and validation fold partitions
        X_train, X_test = X[train], X[test]
        y_train, y_test = y[train], y[test]
        s_train, s_test = s[train], s[test]

        # fit model and generate train and test predictions
        if fit_with_s(e):
            e.fit(X_train, y_train, s_train)
        else:
            e.fit(X_train, y_train)

        train_pred_args = (X_train, s_train) if predict_with_s(e) \
            else (X_train, )
        test_pred_args = (X_test, s_test) if predict_with_s(e) \
            else (X_test, )

        train_pred_prob = e.predict_proba(*train_pred_args)[:, 1]
        train_pred = e.predict(*train_pred_args)
        test_pred_prob = e.predict_proba(*test_pred_args)[:, 1]
        test_pred = e.predict(*test_pred_args)

        # train scores
        performance_scores.append([
            s_name, e_name, i, "train",
            # regular metrics
            roc_auc_score(y_train, train_pred_prob),

            # fairness metrics
            mean_difference(train_pred, s_train)[0],
        ])
        # test scores
        performance_scores.append([
            s_name, e_name, i, "test",
            # regular metrics
            roc_auc_score(y_test, test_pred_prob),
            # fairness metrics
            mean_difference(test_pred, s_test)[0]
        ])
    if verbose:
        print("")
if verbose:
    print("")
return pd.DataFrame(
    performance_scores,
    columns=[
        "protected_class", "estimator", "cv_fold", "fold_type",
```

```python
                  "roc", "mean_diff"])

    # training and target data
    X = german_credit_preprocessed[feature_set_1].values
    y = german_credit_preprocessed["credit_risk"].values
    s_female = german_credit_preprocessed["female"].values
    s_foreign = german_credit_preprocessed["foreign_worker"].values
    s_age_below_25 = german_credit_preprocessed["age_below_25"].values

    LOGISTIC_REGRESSION = LogisticRegression(
        penalty="l2", C=0.001, class_weight="balanced")
    DECISION_TREE_CLF = DecisionTreeClassifier(
        criterion="entropy", max_depth=10, min_samples_leaf=10, max_features=10,
        class_weight="balanced")
    RANDOM_FOREST_CLF = RandomForestClassifier(
        criterion="entropy", n_estimators=50, max_depth=10, max_features=10,
        min_samples_leaf=10, class_weight="balanced")
    estimators = [
        ("LogisticRegression", LOGISTIC_REGRESSION),
        ("DecisionTree", DECISION_TREE_CLF),
        ("RandomForest", RANDOM_FOREST_CLF)
    ]
    experiment_baseline_female = cross_validation_experiment(
        estimators, X, y, s_female, "female")
    experiment_baseline_foreign = cross_validation_experiment(
        estimators, X, y, s_foreign, "foreign_worker")
    experiment_baseline_age_below_25 = cross_validation_experiment(
        estimators, X, y, s_age_below_25, "age_below_25")
```

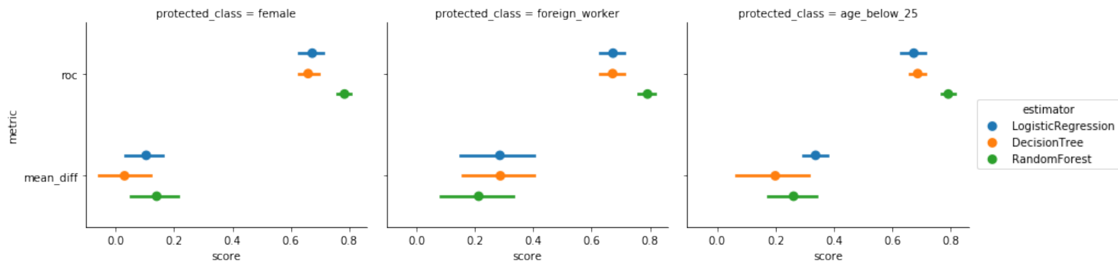
```
Training models: protected_class = female
-----------------------------------------
LogisticRegression, fold: 0 1 2 3 4 5 6 7 8 9
DecisionTree, fold: 0 1 2 3 4 5 6 7 8 9
RandomForest, fold: 0 1 2 3 4 5 6 7 8 9

Training models: protected_class = foreign_worker
-------------------------------------------------
LogisticRegression, fold: 0 1 2 3 4 5 6 7 8 9
DecisionTree, fold: 0 1 2 3 4 5 6 7 8 9
RandomForest, fold: 0 1 2 3 4 5 6 7 8 9

Training models: protected_class = age_below_25
-----------------------------------------------
LogisticRegression, fold: 0 1 2 3 4 5 6 7 8 9
DecisionTree, fold: 0 1 2 3 4 5 6 7 8 9
RandomForest, fold: 0 1 2 3 4 5 6 7 8 9
```

In [15]:
```python
import seaborn as sns
import matplotlib.pyplot as plt
% matplotlib inline

UTILITY_METRICS = ["roc"]
FAIRNESS_METRICS = ["mean_diff"]

def summarize_experiment_results(experiment_df):
    return (
        experiment_df
        .drop("cv_fold", axis=1)
        .groupby(["protected_class", "estimator", "fold_type"])
        .mean())

experiment_baseline = pd.concat([
    experiment_baseline_female,
    experiment_baseline_foreign,
    experiment_baseline_age_below_25
])
experiment_baseline_summary = summarize_experiment_results(
    experiment_baseline)
experiment_baseline_summary.query("fold_type == 'test'")
```

Out[15]:

protected_class	estimator	fold_type	roc	mean_diff
age_below_25	DecisionTree	test	0.686881	0.199053
	LogisticRegression	test	0.673619	0.337183
	RandomForest	test	0.791762	0.261755
female	DecisionTree	test	0.659500	0.030593
	LogisticRegression	test	0.673619	0.104857
	RandomForest	test	0.784143	0.140700
foreign_worker	DecisionTree	test	0.672262	0.287732
	LogisticRegression	test	0.673619	0.286108
	RandomForest	test	0.791857	0.213481

In [16]:
```python
def plot_experiment_results(experiment_results):
    return (
        experiment_results
        .query("fold_type == 'test'")
        .drop(["fold_type", "cv_fold"], axis=1)
        .pipe(pd.melt, id_vars=["protected_class", "estimator"],
              var_name="metric", value_name="score")
        .pipe((sns.factorplot, "data"), y="metric",
              x="score", hue="estimator", col="protected_class", col_wrap=3,
              size=3.5, aspect=1.2, join=False, dodge=0.4))

plot_experiment_results(experiment_baseline);
```



It appears that the variance of `normalized_mean_difference` across the 10 cross-validation folds is higher than `mean_difference`, likely because the normalization factor `d_max` depends on the rate of positive labels in the data.

```
In [17]: from IPython.display import Markdown, display

         def print_best_metrics(experiment_results, protected_classes):
             for pclass in protected_classes:
                 msg = "#### protected class = %s:" % pclass
                 display(Markdown(msg))
                 exp_df = experiment_results[
                     (experiment_results["protected_class"] == pclass) &
                     (experiment_results["fold_type"] == "test")]
                 msg = ""

                 for m in UTILITY_METRICS:
                     utility_msg = \
                         "- best utility measured by %s (higher is better)" % m
                     best_model = (
                         exp_df
                         .sort_values(m, ascending=False)
                         .drop(["fold_type"], axis=1)
                         .iloc[0][[m, "estimator"]])
                     msg += utility_msg + " = %0.03f: %s\n" % \
                            (best_model[0], best_model[1])

                 for m in FAIRNESS_METRICS:
                     fairness_msg = \
                         "- best fairness measured by %s (lower is better)" % m
                     best_model = (
                         exp_df
                         # score closer to zero is better
                         .assign(abs_measure=lambda df: df[m].abs())
                         .sort_values("abs_measure")
                         .drop(["abs_measure", "fold_type"], axis=1)
                         .iloc[0][[m, "estimator"]])
                     msg += fairness_msg + " = %0.03f: %s\n" % \
                            (best_model[0], best_model[1])
```

```
            display(Markdown(msg))

    print_best_metrics(
        experiment_baseline_summary.reset_index(),
        ["female", "foreign_worker", "age_below_25"])
```

protected class = female:

- best utility measured by roc (higher is better) = 0.784: RandomForest
- best fairness measured by mean_diff (lower is better) = 0.031: DecisionTree

protected class = foreign_worker:

- best utility measured by roc (higher is better) = 0.792: RandomForest
- best fairness measured by mean_diff (lower is better) = 0.213: RandomForest

protected class = age_below_25:

- best utility measured by roc (higher is better) = 0.792: RandomForest
- best fairness measured by mean_diff (lower is better) = 0.199: DecisionTree

5 Naive Fairness-aware Approach: Remove Protected Class

The naive approach to training fairness-aware models is to remove the protected class variables from the input data. While at face value this approach might seem like a good measure to prevent the model from learning the discriminatory patterns in the raw data, it doesn't preclude the possibility of other non-protected class variables highly correlate with protected class variables.

An well-known example of this is how `zipcode` correlates with `race`, so `zipcode` essentially serves as a proxy for `race` in the training data even if `race` is excluded from the input data.

```
In [18]: # create feature sets that remove variables with protected class information
         feature_set_no_sex = [
             f for f in feature_set_1 if
             f not in [
                 'personal_status_and_sex_female_divorced/separated/married',
                 'personal_status_and_sex_male_divorced/separated',
                 'personal_status_and_sex_male_married/widowed',
                 'personal_status_and_sex_male_single']]
         feature_set_no_foreign = [f for f in feature_set_1 if f != "foreign_worker"]
         feature_set_no_age = [f for f in feature_set_1 if f != "age_in_years"]
```

```
In [19]: # training and target data
         X_no_sex = german_credit_preprocessed[feature_set_no_sex].values
         X_no_foreign = german_credit_preprocessed[feature_set_no_foreign].values
         X_no_age = german_credit_preprocessed[feature_set_no_age].values

         experiment_naive_female = cross_validation_experiment(
             estimators, X_no_sex, y, s_female, "female")
```

```
        experiment_naive_foreign = cross_validation_experiment(
            estimators, X_no_foreign, y, s_foreign, "foreign_worker")
        experiment_naive_age_below_25 = cross_validation_experiment(
            estimators, X_no_age, y, s_age_below_25, "age_below_25")
```

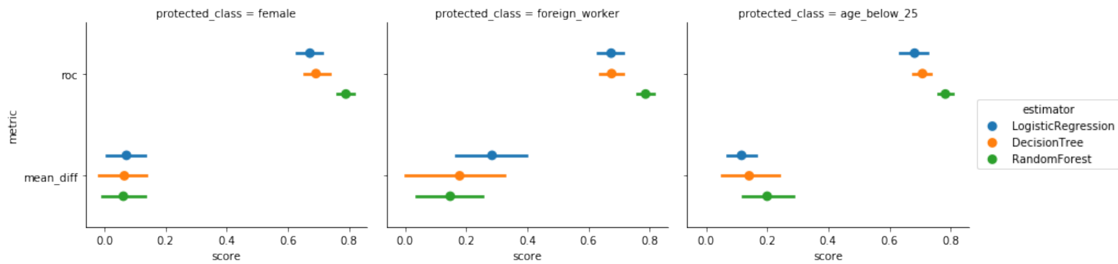
```
Training models: protected_class = female
-----------------------------------------
LogisticRegression, fold: 0 1 2 3 4 5 6 7 8 9
DecisionTree, fold: 0 1 2 3 4 5 6 7 8 9
RandomForest, fold: 0 1 2 3 4 5 6 7 8 9

Training models: protected_class = foreign_worker
-------------------------------------------------
LogisticRegression, fold: 0 1 2 3 4 5 6 7 8 9
DecisionTree, fold: 0 1 2 3 4 5 6 7 8 9
RandomForest, fold: 0 1 2 3 4 5 6 7 8 9

Training models: protected_class = age_below_25
-----------------------------------------------
LogisticRegression, fold: 0 1 2 3 4 5 6 7 8 9
DecisionTree, fold: 0 1 2 3 4 5 6 7 8 9
RandomForest, fold: 0 1 2 3 4 5 6 7 8 9
```

```
In [20]: experiment_naive = pd.concat([
             experiment_naive_female,
             experiment_naive_foreign,
             experiment_naive_age_below_25
         ])
         experiment_naive_summary = summarize_experiment_results(experiment_naive)
         experiment_naive_summary.query("fold_type == 'test'")
```

Out[20]:

protected_class	estimator	fold_type	roc	mean_diff
age_below_25	DecisionTree	test	0.708143	0.141391
	LogisticRegression	test	0.682381	0.116435
	RandomForest	test	0.783095	0.200083
female	DecisionTree	test	0.691976	0.065153
	LogisticRegression	test	0.672238	0.072140
	RandomForest	test	0.789857	0.061928
foreign_worker	DecisionTree	test	0.675238	0.178127
	LogisticRegression	test	0.673667	0.284035
	RandomForest	test	0.786333	0.147360

```
In [21]: plot_experiment_results(experiment_naive);
```




```
In [22]: print_best_metrics(
             experiment_naive_summary.reset_index(),
             ["female", "foreign_worker", "age_below_25"])
```

protected class = female:

- best utility measured by roc (higher is better) = 0.790: RandomForest
- best fairness measured by mean_diff (lower is better) = 0.062: RandomForest

protected class = foreign_worker:

- best utility measured by roc (higher is better) = 0.786: RandomForest
- best fairness measured by mean_diff (lower is better) = 0.147: RandomForest

protected class = age_below_25:

- best utility measured by roc (higher is better) = 0.783: RandomForest
- best fairness measured by mean_diff (lower is better) = 0.116: LogisticRegression

6 Fairness-aware Method: Relabelling

In this and the following fairness-aware modeling runs, we exclude the protected class variables as in the **Naive Fairness-aware Approach** section in addition to the explicit fairness-aware technique.

```
In [23]: from sklearn.base import clone

         from themis_ml.preprocessing.relabelling import Relabeller
         from themis_ml.meta_estimators import FairnessAwareMetaEstimator

         # here we use the relabeller class to create new y vectors for each of the
         # protected class contexts.

         # we also use the FairnessAwareMetaEstimator as a convenience class to
         # compose together different fairness-aware methods. This wraps around the
         # estimators that we defined in the previous
         relabeller = Relabeller()
         relabelling_estimators = [
```

```
        (name, FairnessAwareMetaEstimator(e, relabeller=relabeller))
        for name, e in estimators]

    experiment_relabel_female = cross_validation_experiment(
        relabelling_estimators, X_no_sex, y, s_female, "female")
    experiment_relabel_foreign = cross_validation_experiment(
        relabelling_estimators, X_no_foreign, y, s_foreign, "foreign_worker")
    experiment_relabel_age_below_25 = cross_validation_experiment(
        relabelling_estimators, X_no_age, y, s_age_below_25, "age_below_25")
```

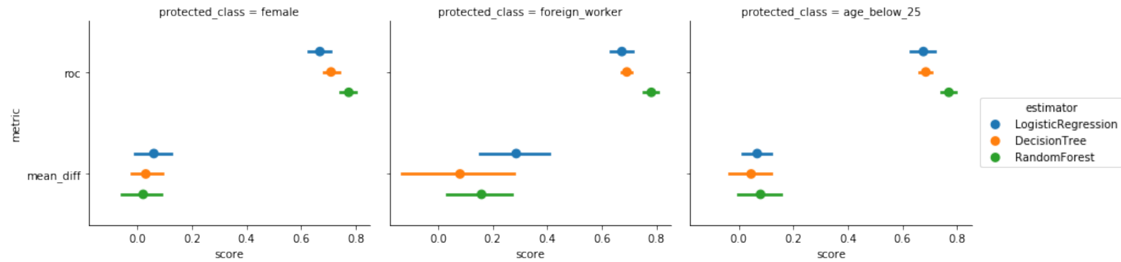
```
Training models: protected_class = female
-----------------------------------------
LogisticRegression, fold: 0 1 2 3 4 5 6 7 8 9
DecisionTree, fold: 0 1 2 3 4 5 6 7 8 9
RandomForest, fold: 0 1 2 3 4 5 6 7 8 9

Training models: protected_class = foreign_worker
-------------------------------------------------
LogisticRegression, fold: 0 1 2 3 4 5 6 7 8 9
DecisionTree, fold: 0 1 2 3 4 5 6 7 8 9
RandomForest, fold: 0 1 2 3 4 5 6 7 8 9

Training models: protected_class = age_below_25
-----------------------------------------------
LogisticRegression, fold: 0 1 2 3 4 5 6 7 8 9
DecisionTree, fold: 0 1 2 3 4 5 6 7 8 9
RandomForest, fold: 0 1 2 3 4 5 6 7 8 9
```

In [24]:
```
experiment_relabel = pd.concat([
    experiment_relabel_female,
    experiment_relabel_foreign,
    experiment_relabel_age_below_25
])
experiment_relabel_summary = summarize_experiment_results(experiment_relabel)
experiment_relabel_summary.query("fold_type == 'test'")
```

Out[24]:

protected_class	estimator	fold_type	roc	mean_diff
age_below_25	DecisionTree	test	0.685167	0.044597
	LogisticRegression	test	0.676429	0.066849
	RandomForest	test	0.769810	0.079129
female	DecisionTree	test	0.710119	0.030668
	LogisticRegression	test	0.669286	0.060313
	RandomForest	test	0.775143	0.021160
foreign_worker	DecisionTree	test	0.691857	0.080055
	LogisticRegression	test	0.673619	0.286160
	RandomForest	test	0.781762	0.158927

```
In [25]: plot_experiment_results(experiment_relabel);
```




```
In [26]: print_best_metrics(
             experiment_relabel_summary.reset_index(),
             ["female", "foreign_worker", "age_below_25"])
```

protected class = female:

- best utility measured by roc (higher is better) = 0.775: RandomForest
- best fairness measured by mean_diff (lower is better) = 0.021: RandomForest

protected class = foreign_worker:

- best utility measured by roc (higher is better) = 0.782: RandomForest
- best fairness measured by mean_diff (lower is better) = 0.080: DecisionTree

protected class = age_below_25:

- best utility measured by roc (higher is better) = 0.770: RandomForest
- best fairness measured by mean_diff (lower is better) = 0.045: DecisionTree

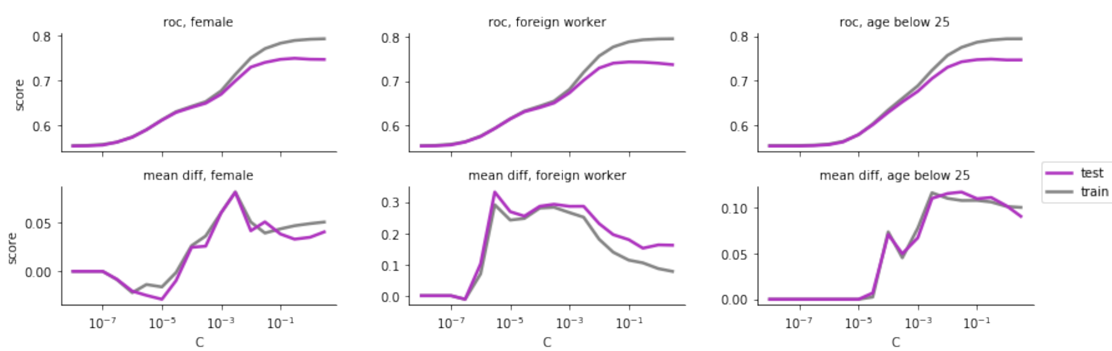
6.0.1 Validation Curve: Logistic Regression

```
In [27]: LOGREG_L2_PARAM = [
             3, 1, 3e-1, 1e-1, 3e-2, 1e-2, 3e-3, 1e-3,
             3e-4, 1e-4, 3e-5, 1e-5, 3e-6, 1e-6, 3e-7, 1e-7, 3e-8, 1e-8]

         def validation_curve_experiment(
                 estimator_name, estimator, param_name, param_list, update_func):
             validaton_curve_experiment = []
             for param in param_list:
                 e = clone(estimator)
                 e = update_func(e, param_name, param)
                 estimators = [(estimator_name, e)]
                 experiment_relabel_female = cross_validation_experiment(
                     estimators, X_no_sex, y, s_female, "female",
                     verbose=False)
```

```
        experiment_relabel_foreign = cross_validation_experiment(
            estimators, X_no_foreign, y, s_foreign, "foreign_worker",
            verbose=False)
        experiment_relabel_age_below_25 = cross_validation_experiment(
            estimators, X_no_age, y, s_age_below_25, "age_below_25",
            verbose=False)
        validaton_curve_experiment.extend(
            [experiment_relabel_female.assign(**{param_name: param}),
             experiment_relabel_foreign.assign(**{param_name: param}),
             experiment_relabel_age_below_25.assign(**{param_name: param})])
    return pd.concat(validaton_curve_experiment)


def update_relabeller(e, param_name, param):
    e = clone(e)
    child_estimator = clone(e.estimator)
    child_estimator.set_params(**{param_name: param})
    e.set_params(estimator=child_estimator)
    return e


relabel_validaton_curve_experiment = validation_curve_experiment(
    "LogisticRegression", FairnessAwareMetaEstimator(
        LOGISTIC_REGRESSION, relabeller=Relabeller()),
    "C", LOGREG_L2_PARAM, update_relabeller)
```

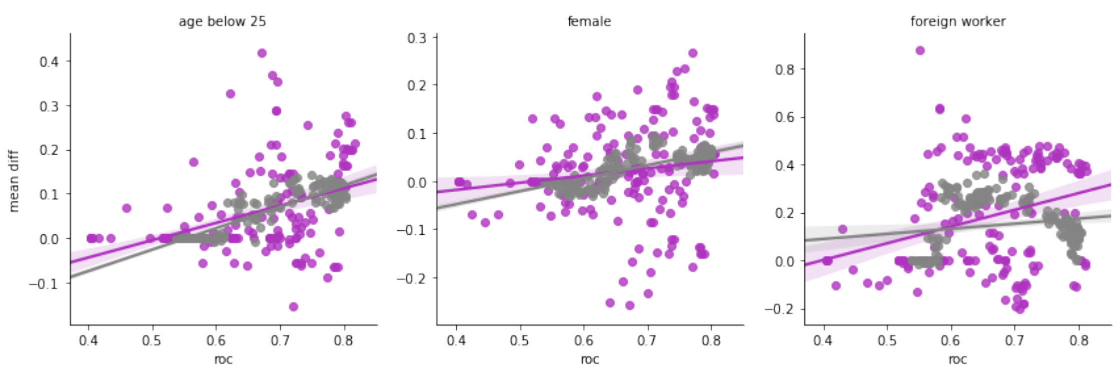
```
In [193]: def validation_curve_plot(x, y, **kwargs):
              ax = plt.gca()
              lw = 2.5
              data = kwargs.pop("data")
              train_data = data.query("fold_type == 'train'")
              test_data = data.query("fold_type == 'test'")
              grp_data_train = train_data.groupby(x)
              grp_data_test = test_data.groupby(x)
              mean_data_train = grp_data_train[y].mean()
              mean_data_test = grp_data_test[y].mean()
              std_data_train = grp_data_train[y].std()
              std_data_test = grp_data_test[y].std()
              ax.semilogx(mean_data_train.index, mean_data_train,
                          label="train", color="#848484", lw=lw)
              ax.semilogx(mean_data_test.index, mean_data_test,
                          label="test", color="#ae33bf", lw=lw)
              # # Add error region
              # ax.fill_between(mean_data_train.index, mean_data_train - std_data_train,
              #                 mean_data_train + std_data_train, alpha=0.2,
              #                 color="darkorange", lw=lw)
              # ax.fill_between(mean_data_test.index, mean_data_test - std_data_test,
              #                 mean_data_test + std_data_test, alpha=0.1,
```

```
#                 color="navy", lw=lw)

relabel_validaton_curve_experiment_df = (
    relabel_validaton_curve_experiment
    .pipe(pd.melt,
          id_vars=["protected_class", "estimator", "cv_fold", "fold_type",
                   "C"],
          value_vars=["roc", "mean_diff"],
          var_name="metric", value_name="score")
    .assign(
        protected_class=lambda df: df.protected_class.str.replace("_", " "),
        metric=lambda df: df.metric.str.replace("_", " ")
    )
)

# relabel_validaton_curve_experiment_df
g = sns.FacetGrid(
    relabel_validaton_curve_experiment_df,
    col="protected_class",
    row="metric", size=2, aspect=2, sharey=False,
    margin_titles=False)
g = g.map_dataframe(validation_curve_plot, "C", "score")
g.set_titles(template="{row_name}, {col_name}")
g.add_legend();
```




```
In [196]: def utility_fairness_corr_plot(x, y, **kwargs):
              ax = plt.gca()
              lw = 2
              data = kwargs.pop("data").sort_values(x)
              data.plot(x, y, ax=ax, kind="scatter", alpha=0.5)

          corr_plot = (
              relabel_validaton_curve_experiment_df
              .pivot_table(
                  index=["protected_class", "estimator", "cv_fold", "fold_type","C"],
```

```
        columns="metric", values="score")
    .reset_index()
)

train_test_palette = sns.color_palette(["#ae33bf", "#848484"])

g = sns.FacetGrid(
    corr_plot,
    col="protected_class",
    hue="fold_type", size=4, aspect=1, sharey=False,
    hue_order=["test", "train"],
    margin_titles=True,
    palette=train_test_palette)
(
    g
    .map(sns.regplot, "roc", "mean diff")
    .set_titles(col_template="{col_name}")
);
```



7 Fairness-aware Method: Additive Counterfactually Fair Model

In [30]:
```
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor

from themis_ml.linear_model.counterfactually_fair_models import \
    LinearACFClassifier

LINEAR_REG = LinearRegression()
DECISION_TREE_REG = DecisionTreeRegressor(max_depth=10, min_samples_leaf=10)
RANDOM_FOREST_REG = RandomForestRegressor(
    n_estimators=50, max_depth=10, min_samples_leaf=10)
```

```python
# use the estimators defined above to define the linear additive
# counterfactually fair models
linear_acf_estimators = [
    (name, LinearACFClassifier(
         target_estimator=e,
         binary_residual_type="absolute"))
    for name, e in estimators]

experiment_acf_female = cross_validation_experiment(
    linear_acf_estimators, X_no_sex, y, s_female, "female")
experiment_acf_foreign = cross_validation_experiment(
    linear_acf_estimators, X_no_foreign, y, s_foreign, "foreign_worker")
experiment_acf_age_below_25 = cross_validation_experiment(
    linear_acf_estimators, X_no_age, y, s_age_below_25, "age_below_25")
```

```
Training models: protected_class = female
-----------------------------------------
LogisticRegression, fold: 0 1 2 3 4 5 6 7 8 9
DecisionTree, fold: 0 1 2 3 4 5 6 7 8 9
RandomForest, fold: 0 1 2 3 4 5 6 7 8 9

Training models: protected_class = foreign_worker
-------------------------------------------------
LogisticRegression, fold: 0 1 2 3 4 5 6 7 8 9
DecisionTree, fold: 0 1 2 3 4 5 6 7 8 9
RandomForest, fold: 0 1 2 3 4 5 6 7 8 9

Training models: protected_class = age_below_25
-----------------------------------------------
LogisticRegression, fold: 0 1 2 3 4 5 6 7 8 9
DecisionTree, fold: 0 1 2 3 4 5 6 7 8 9
RandomForest, fold: 0 1 2 3 4 5 6 7 8 9
```

In [31]:
```python
experiment_acf = pd.concat([
    experiment_acf_female,
    experiment_acf_foreign,
    experiment_acf_age_below_25
])
experiment_acf_summary = summarize_experiment_results(experiment_acf)
experiment_acf_summary.query("fold_type == 'test'")
```

Out[31]:

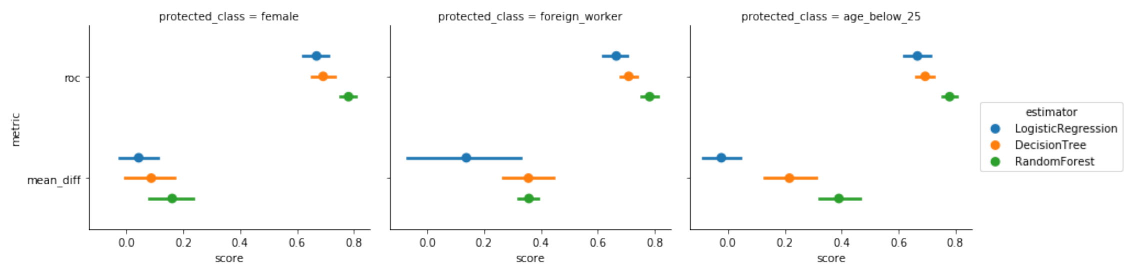
protected_class	estimator	fold_type	roc	mean_diff
age_below_25	DecisionTree	test	0.693690	0.216496
	LogisticRegression	test	0.666381	-0.022842
	RandomForest	test	0.779524	0.390385

```
female          DecisionTree       test      0.691976   0.087840
                LogisticRegression test      0.668810   0.043642
                RandomForest       test      0.781190   0.161307
foreign_worker  DecisionTree       test      0.708810   0.356341
                LogisticRegression test      0.665190   0.138082
                RandomForest       test      0.782333   0.358109
```

In [32]:
```python
experiment_acf = pd.concat([
    experiment_acf_female,
    experiment_acf_foreign,
    experiment_acf_age_below_25
])
experiment_acf_summary = summarize_experiment_results(experiment_acf)
experiment_acf_summary.query("fold_type == 'test'")
```

Out[32]:
```
                                                         roc  mean_diff
protected_class estimator          fold_type
age_below_25    DecisionTree       test      0.693690   0.216496
                LogisticRegression test      0.666381  -0.022842
                RandomForest       test      0.779524   0.390385
female          DecisionTree       test      0.691976   0.087840
                LogisticRegression test      0.668810   0.043642
                RandomForest       test      0.781190   0.161307
foreign_worker  DecisionTree       test      0.708810   0.356341
                LogisticRegression test      0.665190   0.138082
                RandomForest       test      0.782333   0.358109
```

In [33]:
```python
plot_experiment_results(experiment_acf);
```



In [34]:
```python
print_best_metrics(
    experiment_acf_summary.reset_index(),
    ["female", "foreign_worker", "age_below_25"])
```

protected class = female:

- best utility measured by roc (higher is better) = 0.781: RandomForest
- best fairness measured by mean_diff (lower is better) = 0.044: LogisticRegression

protected class = foreign_worker:

- best utility measured by roc (higher is better) = 0.782: RandomForest
- best fairness measured by mean_diff (lower is better) = 0.138: LogisticRegression

protected class = age_below_25:

- best utility measured by roc (higher is better) = 0.780: RandomForest
- best fairness measured by mean_diff (lower is better) = -0.023: LogisticRegression

8 Fairness-aware Method: Reject-option Classification

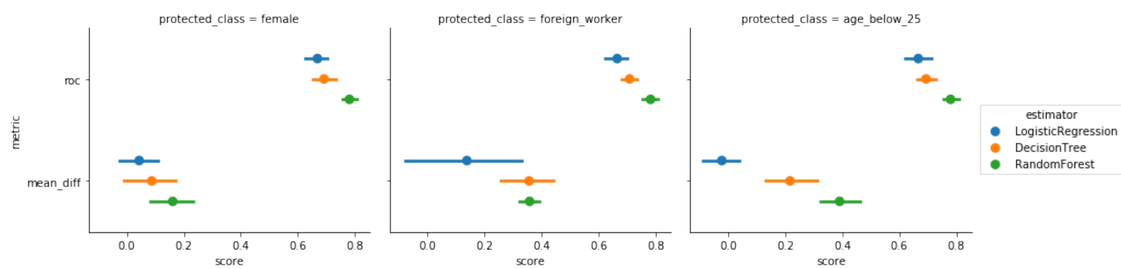
```
In [35]: from themis_ml.postprocessing.reject_option_classification import \
             SingleROClassifier

         # use the estimators defined above to define the linear additive
         # counterfactually fair models
         single_roc_clf_estimators = [
             (name, SingleROClassifier(estimator=e))
             for name, e in estimators]

         experiment_single_roc_female = cross_validation_experiment(
             single_roc_clf_estimators, X_no_sex, y, s_female, "female")
         experiment_single_roc_foreign = cross_validation_experiment(
             single_roc_clf_estimators, X_no_foreign, y, s_foreign, "foreign_worker")
         experiment_single_roc_age_below_25 = cross_validation_experiment(
             single_roc_clf_estimators, X_no_age, y, s_age_below_25, "age_below_25")
```

```
Training models: protected_class = female
-----------------------------------------
LogisticRegression, fold: 0 1 2 3 4 5 6 7 8 9
DecisionTree, fold: 0 1 2 3 4 5 6 7 8 9
RandomForest, fold: 0 1 2 3 4 5 6 7 8 9

Training models: protected_class = foreign_worker
-------------------------------------------------
LogisticRegression, fold: 0 1 2 3 4 5 6 7 8 9
DecisionTree, fold: 0 1 2 3 4 5 6 7 8 9
RandomForest, fold: 0 1 2 3 4 5 6 7 8 9

Training models: protected_class = age_below_25
-----------------------------------------------
LogisticRegression, fold: 0 1 2 3 4 5 6 7 8 9
DecisionTree, fold: 0 1 2 3 4 5 6 7 8 9
RandomForest, fold: 0 1 2 3 4 5 6 7 8 9
```

```
In [36]: experiment_single_roc = pd.concat([
             experiment_single_roc_female,
             experiment_single_roc_foreign,
             experiment_single_roc_age_below_25
         ])
         experiment_single_roc_summary = summarize_experiment_results(
             experiment_single_roc)
         experiment_single_roc_summary.query("fold_type == 'test'")
```

```
Out[36]:                                                    roc  mean_diff
         protected_class estimator          fold_type
         age_below_25    DecisionTree       test       0.681738   0.086971
                         LogisticRegression test       0.539905  -0.047437
                         RandomForest       test       0.764048   0.065078
         female          DecisionTree       test       0.690595   0.080805
                         LogisticRegression test       0.608524  -0.049494
                         RandomForest       test       0.761333   0.062303
         foreign_worker  DecisionTree       test       0.695190   0.093653
                         LogisticRegression test       0.619429   0.032667
                         RandomForest       test       0.748000   0.074623
```

```
In [37]: plot_experiment_results(experiment_acf);
```




```
In [38]: print_best_metrics(
             experiment_acf.reset_index(),
             ["female", "foreign_worker", "age_below_25"])
```

protected class = female:

- best utility measured by roc (higher is better) = 0.840: RandomForest
- best fairness measured by mean_diff (lower is better) = 0.019: LogisticRegression

protected class = foreign_worker:

- best utility measured by roc (higher is better) = 0.849: RandomForest
- best fairness measured by mean_diff (lower is better) = 0.021: DecisionTree

protected class = age_below_25:

- best utility measured by roc (higher is better) = 0.851: RandomForest
- best fairness measured by mean_diff (lower is better) = 0.009: DecisionTree

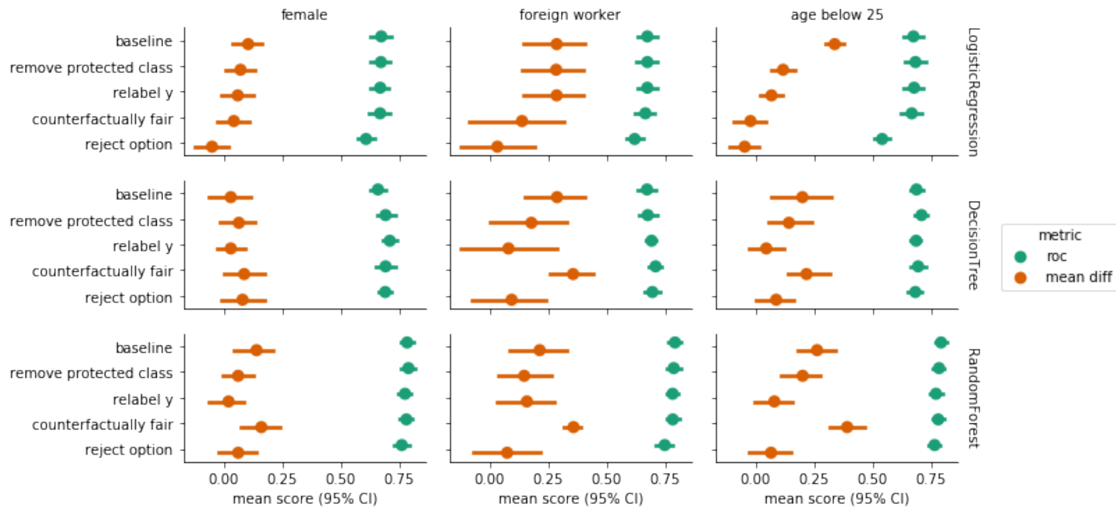
9 Comparison of Fairness-aware Techniques

In [201]:
```
compare_experiments = (
    pd.concat([
        experiment_baseline.assign(experiment="baseline"),
        experiment_naive.assign(experiment="remove protected class"),
        experiment_relabel.assign(experiment="relabel y"),
        experiment_acf.assign(experiment="counterfactually fair"),
        experiment_single_roc.assign(experiment="reject option")
    ])
    .assign(
        protected_class=lambda df: df.protected_class.str.replace("_", " "),
#          metric=lambda df: df.metric.str.replace("_", " ")
    )
)
compare_experiments.head()
```

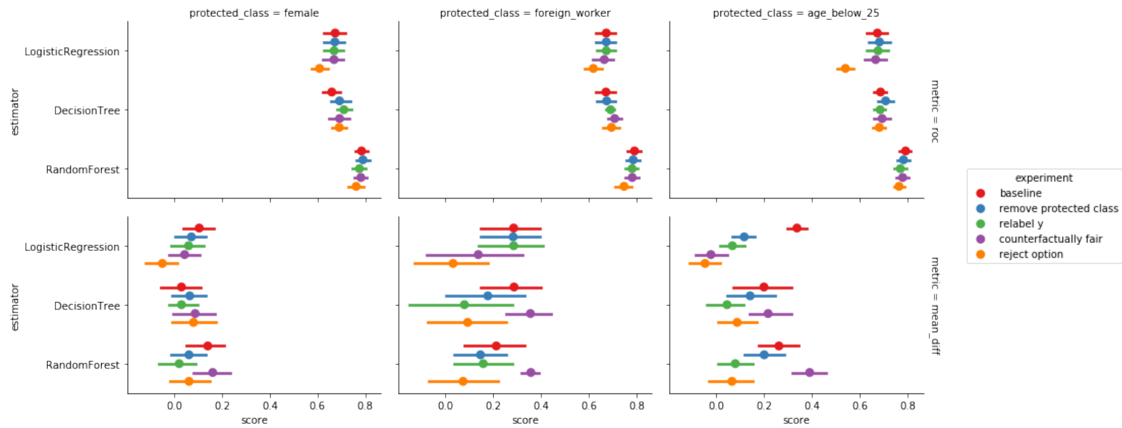
Out[201]:
```
  protected_class           estimator  cv_fold fold_type       roc  mean_diff  \
0          female  LogisticRegression        0     train  0.676490   0.094124
1          female  LogisticRegression        0      test  0.742857   0.261905
2          female  LogisticRegression        1     train  0.683892   0.090553
3          female  LogisticRegression        1      test  0.624286   0.119048
4          female  LogisticRegression        2     train  0.678025   0.115808

  experiment
0   baseline
1   baseline
2   baseline
3   baseline
4   baseline
```

In [255]:
```
comparison_palette = sns.color_palette("Dark2", n_colors=8)

def compare_experiment_results_single_model(experiment_results):
    g = (
        experiment_results
        .query("fold_type == 'test'")
        .drop(["cv_fold"], axis=1)
        .pipe(pd.melt, id_vars=["experiment", "protected_class", "estimator",
                                "fold_type"],
              var_name="metric", value_name="score")
        .assign(
            metric=lambda df: df.metric.str.replace("_", " "))
```

```
            .pipe((sns.factorplot, "data"), y="experiment",
                  x="score", hue="metric",
                  col="protected_class", row="estimator",
                  join=False, size=1.75, aspect=2, dodge=0.3,
                  palette=comparison_palette, margin_titles=True))
        g.set_axis_labels("mean score (95% CI)")
        for ax in g.axes.ravel():
            ax.set_ylabel("")
            plt.setp(ax.texts, text="")
        g.set_titles(row_template="{row_name}", col_template="{col_name}")

    compare_experiment_results_single_model(
        compare_experiments);
```




```
In [163]: experiment_palette = sns.color_palette("Set1", n_colors=8)

          def compare_experiment_results(experiment_results):
              return (
                  experiment_results
                  .query("fold_type == 'test'")
                  .drop(["fold_type", "cv_fold"], axis=1)
                  .pipe(pd.melt, id_vars=["experiment", "protected_class", "estimator"],
                        var_name="metric", value_name="score")
                  .pipe((sns.factorplot, "data"), y="estimator",
                        x="score", hue="experiment",
                        col="protected_class", row="metric",
                        join=False, size=3, aspect=1.5, dodge=0.6,
                        margin_titles=True, palette=experiment_palette))

          compare_experiment_results(compare_experiments);
```

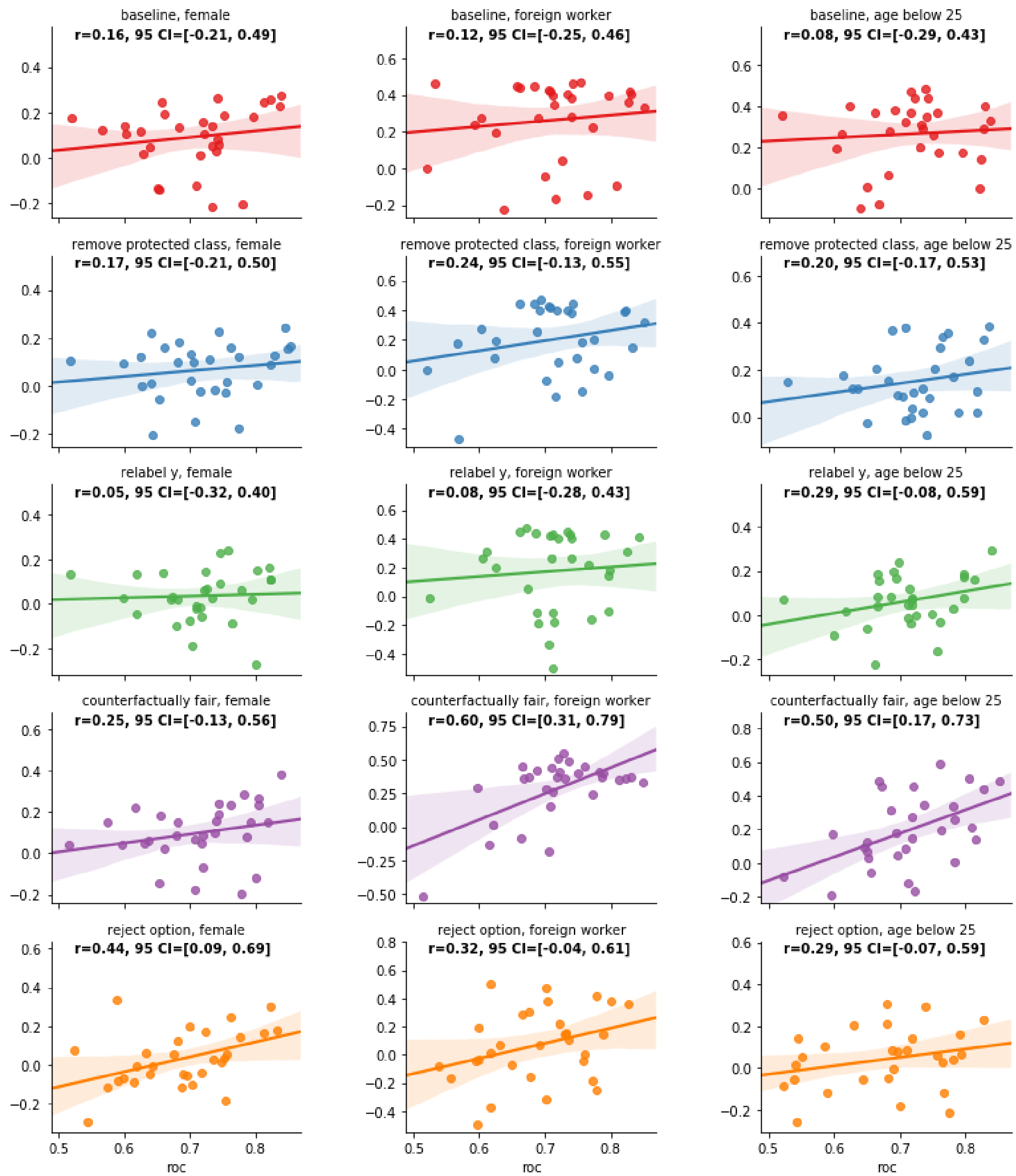


We can make some interesting observations when comparing the results from different fairness-aware techniques.

```
In [105]: from scipy import stats

          def compute_corr_pearson(x, y, ci=0.95):
              corr = stats.pearsonr(x, y)
              z = np.arctanh(corr[0])
              sigma = (1 / ((len(x) - 3) ** 0.5))
              cint = z + np.array([-1, 1]) * sigma * stats.norm.ppf((1 + ci ) / 2)
              return corr, np.tanh(cint)

In [252]: def plot_utility_fairness_tradeoff(x, y, **kwargs):
              ax = plt.gca()
              data = kwargs.pop("data")
              sns_ax = sns.regplot(x=x, y=y, data=data, **kwargs)
              (corr, p_val), ci = compute_corr_pearson(data[x], data[y])
              r_text = 'r=%0.02f, 95 CI=[%0.02f, %0.02f]' % \
                  (corr, ci[0], ci[1])
              sns_ax.annotate(
                  r_text, xy=(0.7, 0),
                  xytext=(0.09, 0.94),
                  textcoords='axes fraction',
                  fontweight="bold",
              )
              bottom_padding = 0.05
              top_padding = 0.3
              ylim = (data[y].min() - bottom_padding, data[y].max() + top_padding)
              sns_ax.set_ylim(*ylim)


          g = sns.FacetGrid(
              (
```

```
                compare_experiments
                .drop("cv_fold", axis=1)
                .reset_index()
                .query("fold_type == 'test'")
            ),
            col="protected_class",
            row="experiment",
            hue="experiment", size=2.5, aspect=1.5, sharey=False,
            palette=experiment_palette)
        # g.map(sns.regplot, "roc", "mean_diff", ci=None);
        g.map_dataframe(plot_utility_fairness_tradeoff, "roc", "mean_diff")
        for ax in g.axes.ravel():
            ax.set_ylabel("")
            anno = ax.texts[0]
            print anno.
        #     plt.setp(ax.texts, text="")
        g.set_titles(template="{row_name}, {col_name}")
        g.fig.tight_layout()
```

```
Annotation(0.7,0,u'r=0.16, 95 CI=[-0.21, 0.49]')
Annotation(0.7,0,u'r=0.12, 95 CI=[-0.25, 0.46]')
Annotation(0.7,0,u'r=0.08, 95 CI=[-0.29, 0.43]')
Annotation(0.7,0,u'r=0.17, 95 CI=[-0.21, 0.50]')
Annotation(0.7,0,u'r=0.24, 95 CI=[-0.13, 0.55]')
Annotation(0.7,0,u'r=0.20, 95 CI=[-0.17, 0.53]')
Annotation(0.7,0,u'r=0.05, 95 CI=[-0.32, 0.40]')
Annotation(0.7,0,u'r=0.08, 95 CI=[-0.28, 0.43]')
Annotation(0.7,0,u'r=0.29, 95 CI=[-0.08, 0.59]')
Annotation(0.7,0,u'r=0.25, 95 CI=[-0.13, 0.56]')
Annotation(0.7,0,u'r=0.60, 95 CI=[0.31, 0.79]')
Annotation(0.7,0,u'r=0.50, 95 CI=[0.17, 0.73]')
Annotation(0.7,0,u'r=0.44, 95 CI=[0.09, 0.69]')
Annotation(0.7,0,u'r=0.32, 95 CI=[-0.04, 0.61]')
Annotation(0.7,0,u'r=0.29, 95 CI=[-0.07, 0.59]')
```




```
In [ ]: def validation_curve_plot(x, y, **kwargs):
            ax = plt.gca()
            lw = 2.5
            data = kwargs.pop("data")
            train_data = data.query("fold_type == 'train'")
            test_data = data.query("fold_type == 'test'")
            grp_data_train = train_data.groupby(x)
            grp_data_test = test_data.groupby(x)
```

```python
    mean_data_train = grp_data_train[y].mean()
    mean_data_test = grp_data_test[y].mean()
    std_data_train = grp_data_train[y].std()
    std_data_test = grp_data_test[y].std()
    ax.semilogx(mean_data_train.index, mean_data_train,
                label="train", color="#ff8930", lw=lw)
    ax.semilogx(mean_data_test.index, mean_data_test,
                label="test", color="#48b5a4", lw=lw)
    # # Add error region
    # ax.fill_between(mean_data_train.index, mean_data_train - std_data_train,
    #                  mean_data_train + std_data_train, alpha=0.2,
    #                  color="darkorange", lw=lw)
    # ax.fill_between(mean_data_test.index, mean_data_test - std_data_test,
    #                  mean_data_test + std_data_test, alpha=0.1,
    #                  color="navy", lw=lw)

relabel_validaton_curve_experiment_df = (
    relabel_validaton_curve_experiment
    .pipe(pd.melt,
          id_vars=["protected_class", "estimator", "cv_fold", "fold_type",
                   "C"],
          value_vars=["roc", "mean_diff"],
          var_name="metric", value_name="score")
)

# relabel_validaton_curve_experiment_df
g = sns.FacetGrid(
    relabel_validaton_curve_experiment_df,
    col="protected_class",
    row="metric", size=2, aspect=2, sharey=False,
    margin_titles=True)
g = g.map_dataframe(validation_curve_plot, "C", "score")
g.add_legend();
```