CPSC 330 midterm

The University of British Columbia

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Please write your CS ID (a.g. a1b2c) **clearly and legibly** at the left-hand side of the box below:

In this exam we'll be analyzing the Rain in Australia dataset from Kaggle. This exam consists of 14 **equally weighted** questions interspersed between parts of the analysis. The exam was printed directly from Jupyter; that is, all the output you see was generated by the code you see, with no "tampering" after-the-fact.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
plt.rcParams['font.size'] = 16
import graphviz
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OrdinalEncoder, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.dummy import DummyClassifier
from sklearn.tree import DecisionTreeClassifier, export_graphviz
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import plot_confusion_matrix, roc_curve, roc_auc_score
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
```

In [2]:
```
pd.set_option('precision', 2)
```

The last line (above) tells pandas to print numbers to 2 decimal places (the default is 6 places). This should improve readability for you.

Preliminaries

Load the data:

In [3]:
```
df = pd.read_csv('weatherAUS.csv', parse_dates=['Date'])
```

Split the data by date (you can assume this is a reasonable thing to do):

In [4]:
```
df_train = df.query('Date <= 20121231')
df_valid = df.query('20130101 <= Date <= 20151231')
df_test  = df.query('Date >= 20160101')
```

First, I call `df.describe()` to get a sense of some of the features:

In [5]:
```
df.describe()
```

Out[5]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am	WindSpeed3pm
count	141556.00	141871.00	140787.00	81350.00	74377.00	132923.00	140845.00	139563.00
mean	12.19	23.23	2.35	5.47	7.62	39.98	14.00	18.64
std	6.40	7.12	8.47	4.19	3.78	13.59	8.89	8.80
min	-8.50	-4.80	0.00	0.00	0.00	6.00	0.00	0.00
25%	7.60	17.90	0.00	2.60	4.90	31.00	7.00	13.00
50%	12.00	22.60	0.00	4.80	8.50	39.00	13.00	19.00
75%	16.80	28.20	0.80	7.40	10.60	48.00	19.00	24.00
max	33.90	48.10	371.00	145.00	14.50	135.00	130.00	87.00

It's interesting to note that the max temperature was 48 degrees; that's very hot!

Q1

What did I do wrong in the above line, and what should I have done instead? **Maximum 2 sentences.**

BEGIN SOLUTION

I should be looking at `df_train` instead of `df`; this is a minor violation of the Golden Rule. For example, that max temperature of 48 may have come from the test set, in which case I shouldn't be allowed to know about it.

END SOLUTION

Next I create X and y. Note: the dataset documentation says to remove `RISK_MM`. I will also drop the `Date`.

In [6]:
```
target_column = 'RainTomorrow'
drop_columns = ['RISK_MM', 'Date']
X_train = df_train.drop(columns=[target_column] + drop_columns)
X_valid = df_valid.drop(columns=[target_column] + drop_columns)
X_test  = df_test.drop( columns=[target_column] + drop_columns)
```

In [7]:
```
y_train = df_train[target_column]
y_valid = df_valid[target_column]
y_test = df_test[target_column]
```

Start looking at the data:

In [8]:
```
X_train.shape
```

Out[8]:
```
(65491, 21)
```

In [9]:
```
X_train
```

Out[9]:

	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed	WindDir9
0	Albury	13.4	22.9	0.6	NaN	NaN	W	44.0	
1	Albury	7.4	25.1	0.0	NaN	NaN	WNW	44.0	NI
2	Albury	12.9	25.7	0.0	NaN	NaN	WSW	46.0	
3	Albury	9.2	28.0	0.0	NaN	NaN	NE	24.0	
4	Albury	17.5	32.3	1.0	NaN	NaN	W	41.0	I
...	...	...	...	...	...	...	...	...	
137500	Darwin	25.0	35.4	0.0	7.4	11.7	N	39.0	N
137501	Darwin	26.5	35.9	0.0	8.0	10.3	N	35.0	
137502	Darwin	27.4	35.0	0.0	7.8	6.5	WNW	31.0	
137503	Darwin	24.8	33.5	3.4	7.4	4.7	E	43.0	I
137504	Darwin	24.5	34.9	0.2	7.0	9.2	N	35.0	

65491 rows × 21 columns

In [10]:
```
numeric_features = ['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine', 'WindGustSpeed'
categorical_features = ['Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm', 'RainToday']
```

Make sure all columns are accounted for:

In [11]:
```
all_features = numeric_features + categorical_features
```

In [12]:
```
assert set(X_train.columns) == set(all_features)
```

Next, I perform similar transformations to what you've seen in the course, using `SimpleImputer`, `StandardScaler`, and `OneHotEncoder`.

In [13]:
```
imputers = [('num', SimpleImputer(strategy='median'), numeric_features),
    ('cat', SimpleImputer(strategy='most_frequent'), categorical_features)]
```

In [14]:
```
impute_transformer = ColumnTransformer(transformers=imputers)
```

In [15]:
```
impute_transformer.fit(X_train);
```

In [16]:
```
X_train_imp = pd.DataFrame(impute_transformer.transform(X_train), index=X_train.index, columns=a
X_valid_imp = pd.DataFrame(impute_transformer.transform(X_valid), index=X_valid.index, columns=a
X_test_imp  = pd.DataFrame(impute_transformer.transform(X_test),  index=X_test.index,  columns=a
```

Below, we use `drop='first'` for all the columns except 'Location':

In [17]:
```
transformers=[
    ('scale', StandardScaler(), numeric_features),
    ('ohe1', OneHotEncoder(sparse=False, handle_unknown='ignore'), ['Location']),
    ('ohe2', OneHotEncoder(sparse=False, drop='first'), categorical_features[1:])]
```

In [18]:
```
preprocessor = ColumnTransformer(transformers=transformers)
```

In [19]:
```
preprocessor.fit(X_train_imp);
```

In [20]:
```
new_columns = numeric_features + list(preprocessor.named_transformers_['ohe1'].get_feature_names
```

In [21]:
```
X_train_transformed = pd.DataFrame(preprocessor.transform(X_train_imp), index=X_train_imp.index,
X_valid_transformed = pd.DataFrame(preprocessor.transform(X_valid_imp), index=X_valid_imp.index,
X_test_transformed  = pd.DataFrame(preprocessor.transform(X_test_imp),  index=X_test_imp.index,
```

Q2

The `RainToday` feature is binary: it only takes on the values "Yes" or "No". I used `OneHotEncoder` to one-hot encode this feature with `drop='first'`. What differences we would observe, if any, had we instead used `OrdinalEncoder` for `RainToday`? Briefly justify your answer. **Maximum 2 sentences.**

BEGIN SOLUTION

We would have had the exact same results either way: one columns, with one category encoded as "0" and the other encoded as "1".

END SOLUTION

Next, I'll use a `DummyClassifier` like the one you implemented in hw4:

In [22]:
```
dc = DummyClassifier(strategy='prior')
dc.fit(X_train_transformed, y_train);
```

In [23]:
```
dc.score(X_train_transformed, y_train)
```

Out[23]:
```
0.7669756149699959
```

In [24]:
```
dc.score(X_valid_transformed, y_valid)
```

Out[24]:
```
0.7896625137990854
```

Q3

Given the above, quantify the level of class imbalance in this dataset. Briefly justify your answer. **Maximum 2 sentences.**

BEGIN SOLUTION

There is around 77% of one class and 23% of the other class, or close to 3:1. A bit imbalanced but not terribly so.

END SOLUTION

Next, we fit a `DecisionTreeClassifier` where the maximum depth of the tree is 2. We set `max_features=5` only because it makes the exam question more interesting, not because it's a good idea.

In [25]:

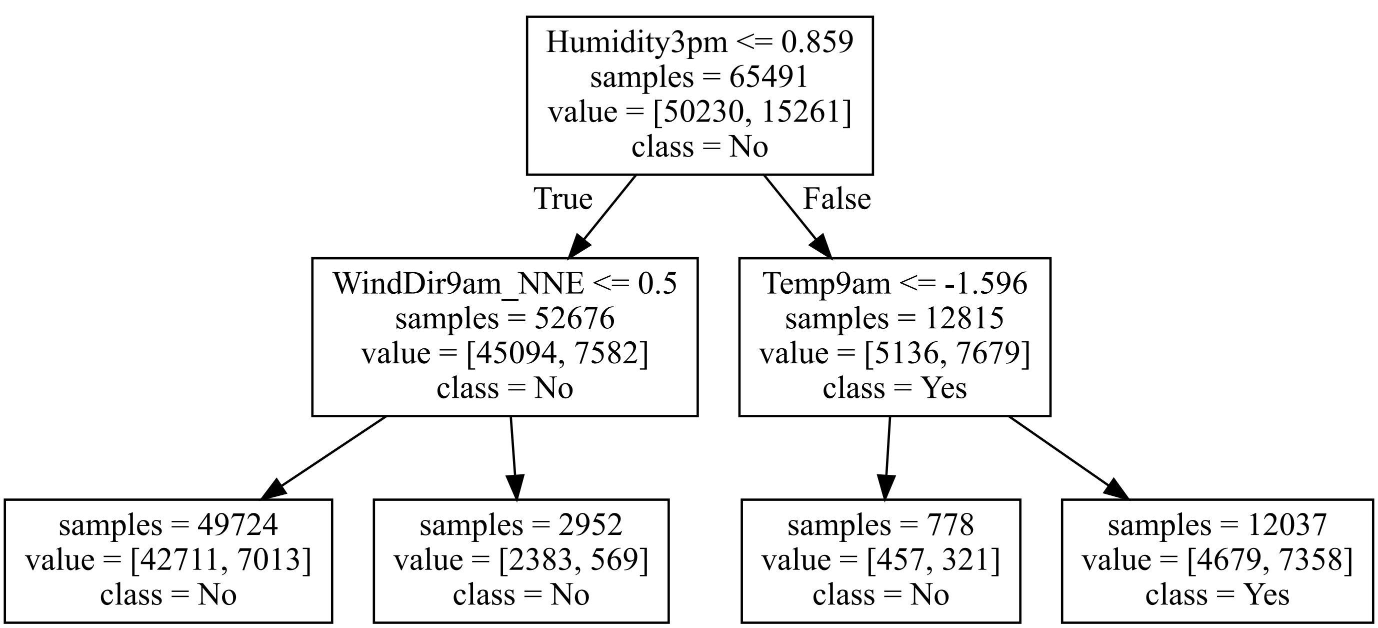
```
dt = DecisionTreeClassifier(max_depth=2, max_features=5, random_state=321)
dt.fit(X_train_transformed, y_train);
```

We then visualize the tree:

In [26]:

```
graphviz.Source(export_graphviz(dt, out_file=None, feature_names=new_columns,
                                class_names=dt.classes_, impurity=False))
```

Out[26]:



Note: for some reason, the arrows are not labeled on the second level, but you can assume that the left side branch is always True and the right branch is always False. So, the 4 arrows in the second level should be labelled True, False, True, False if reading from left to right.

Here is the first element of the validation set. First I print out (a subset of) the **transformed** numerical variables:

In [27]:
```
X_valid_transformed[numeric_features].iloc[:1,9:]
```

Out[27]:

	Humidity3pm	Pressure9am	Pressure3pm	Cloud9am	Cloud3pm	Temp9am	Temp3pm
1416	-1.79	-0.7	-0.88	0.19	0.16	0.89	1.71

And then I print out the **un-transformed** categorical features:

In [28]:
```
X_valid[categorical_features].iloc[:1]
```

Out[28]:

	Location	WindGustDir	WindDir9am	WindDir3pm	RainToday
1416	Albury	W	SE	W	No

Q4

Describe the path of this example down the tree. Which of the four bottom nodes does it end up at: the 1st, 2nd, 3rd or 4th? **Maximum 3 sentences.**

BEGIN SOLUTION

`Humidity3pm <= 0.859` is True, so we go left. `WindDir9am` is "SE", so `WindDir9am_NNE <= 0.5` is True. Thus, we end up at the **1st** node.

END SOLUTION

The following code grabs 4 numeric features - but I'm not telling you which ones.

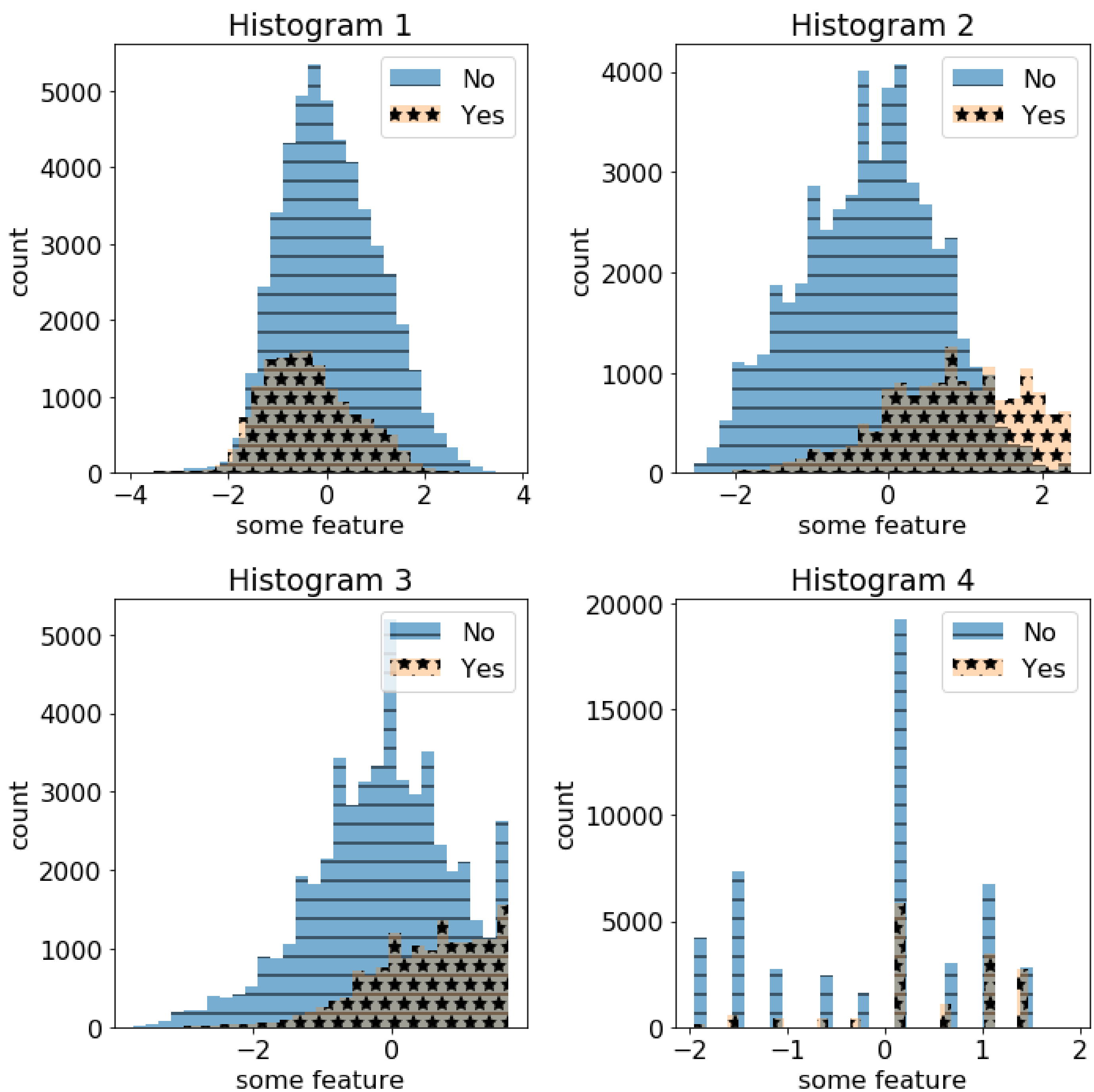
In [29]:
```
np.random.seed(1) # set random state
some_numeric_features = np.random.permutation(numeric_features)[10:14]
```

In hw2, for the spotify dataset, you looked at histograms of various feature values split up by target class. The following code creates 4 such histograms, one for each of the 4 randomly chosen numeric features, using the training set.

In [64]:
```
X_train_neg = X_train_transformed[y_train == "No"]
X_train_pos = X_train_transformed[y_train == "Yes"]

plt.figure(figsize=(10,10))
for i, feature in enumerate(some_numeric_features):

    plt.subplot(2,2,i+1)
    plt.hist(X_train_neg[feature], alpha=0.6, bins=30, label="No", hatch="-")
    plt.hist(X_train_pos[feature], alpha=0.3, bins=30, label="Yes", hatch="*")
    plt.legend(loc='upper right')
    plt.xlabel('some feature')
    plt.ylabel("count")
    plt.title(f"Histogram {i+1}")
plt.tight_layout();
```



Q5

I haven't told you which feature is being used to generate each histogram. Based on the decision tree visualization above, which of the 4 histograms (Histogram 1, Histogram 2, Histogram 3, or Histogram 4) do you think corresponds to the feature `Humidity3pm`? Briefly justify your answer. **Maximum 3 sentences.**

Hint: `Humidity3pm <= 0.859` was chosen by `DecisionTreeClassifier` to be the very first split (i.e., it's at the top of the tree). This indicates that it's a useful split for separating the classes.

BEGIN SOLUTION

We can assume `Humidity3pm` is a relatively important feature since it was chosen as the first split. This makes me suspect **Histogram 2** because there is a more clear division between the classes than the other histograms. The fact that the threshold is close to 1.0 (it's 0.859) provides more evidence that it's probably Histogram 2.

Since we have access to the random permutation, we can verify this:

In [31]:
```
some_numeric_features
```

Out[31]:
```
array(['Temp3pm', 'Humidity3pm', 'Humidity9am', 'Cloud9am'], dtype='<U13')
```

And we see it's indeed the second one.

END SOLUTION

Next, I'll fit a logistic regression:

In [32]:
```
lr = LogisticRegression(max_iter=200)
lr.fit(X_train_transformed, y_train);
```

In [33]:
```
lr.score(X_train_transformed, y_train)
```

Out[33]:
```
0.8466201462796414
```

In [34]:
```
lr.score(X_valid_transformed, y_valid)
```

Out[34]: 0.853887399463807

Q6

Given the above, would it make more sense to try increasing or decreasing the `C` hyperparameter? As a reminder, increasing `C` increases model complexity. Briefly justify your answer. **Maximum 2 sentences.**

BEGIN SOLUTION

The model does not seem to be overfitting whatsoever, so I would not decrease `C`. Thus, **increasing** makes more sense.

END SOLUTION

The following are some of the coefficients learned by `LogisticRegression` (only some of them are shown):

In [35]:
```
pd.DataFrame(data=lr.coef_[0], index=X_train_transformed.columns, columns=["Coefficient"])
```

Out[35]:

	Coefficient
MinTemp	0.11
MaxTemp	-0.56
Rainfall	0.11
Evaporation	0.05
Sunshine	-0.33
...	...
WindDir3pm_SW	-0.05
WindDir3pm_W	0.03
WindDir3pm_WNW	0.15
WindDir3pm_WSW	-0.05
RainToday_Yes	0.45

108 rows × 1 columns

Q7

You will notice that `Evaporation` has a positive coefficient. True or False: increasing the `Evaporation` value (and leaving all other features fixed) will increased the predicted probability that it will rain tomorrow (i.e., the positive class). Briefly justify your answer. **Maximum 2 sentences.**

BEGIN SOLUTION

True, that is the interpretation of a positive coefficient - larger values lead to larger predicted probabilities of the positive class.

END SOLUTION

Q8

You will notice that `WindDir3pm_W`, which is a binary variable created by the `OneHotEncoder`, has a positive coefficient. True or False: an observation with `WindDir3pm` equal to 'W' will have a higher predicted probability that it will rain tomorrow (i.e., the positive class) than an observation with `WindDir3pm` equal to any other value (leaving all other original features fixed). Briefly justify your answer. **Maximum 2 sentences.**

BEGIN SOLUTION

False, for example `WindDir3pm_WNW` has a higher coefficient than `WindDir3pm_W`, so changing from 'WNW' to 'W' would actually lower the predicted probability.

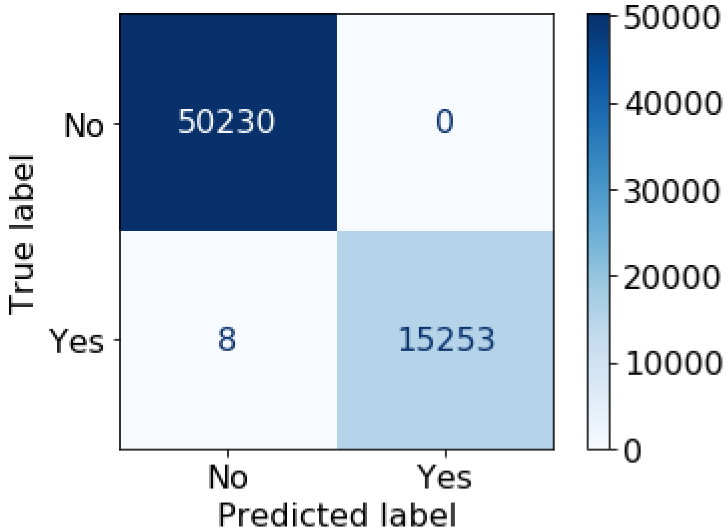
END SOLUTION

Next I will train a random forest on this dataset:

In [36]:
```
rf = RandomForestClassifier(random_state=123)
rf.fit(X_train_transformed, y_train);
```

Here's the confusion matrix based on the **training** set:

In [37]:
```
disp = plot_confusion_matrix(rf, X_train_transformed, y_train,
                             display_labels=rf.classes_,
                             cmap=plt.cm.Blues,
                             values_format = 'd');
```



Q9

Suppose we re-ran the code but with `class_weight="balanced"`. In that case, would you expect the number in the **lower-left** box to increase or decrease? Briefly justify your answer. **Maximum 3 sentences.**

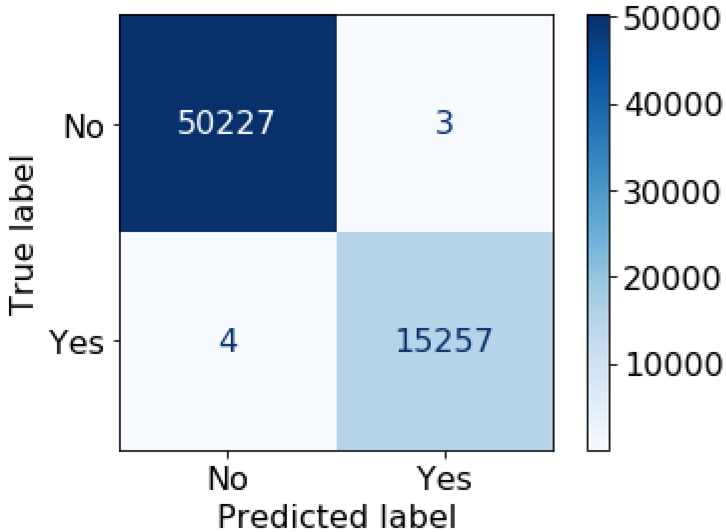
Hint: as a reminder, `class_weight="balanced"` increases the "weight" (or importance) of examples in the minority class.

BEGIN SOLUTION

From the confusion matrix we see there are more instances of "No" than "Yes" (it is Australia after all!). So, setting `class_weight="balanced"` would cause us to predict more "Yes". Thus, the lower-left number should **decrease**.

We can also test it out:

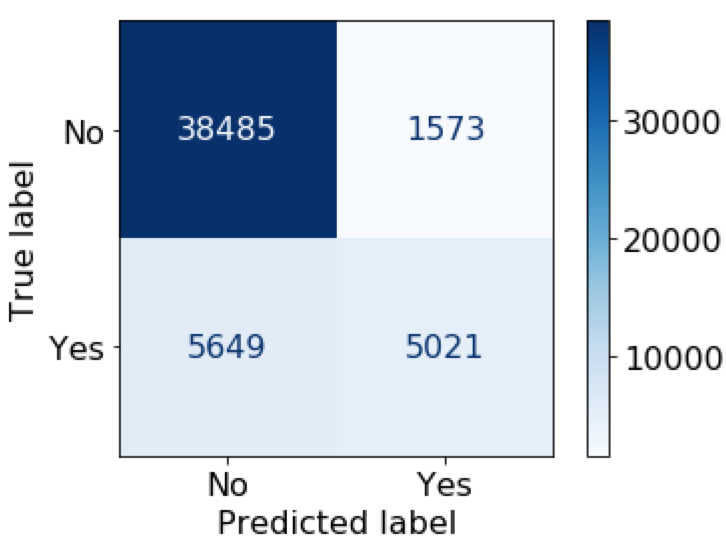
In [38]:
```
rf_balanced_solution = RandomForestClassifier(class_weight="balanced", random_state=123)
rf_balanced_solution.fit(X_train_transformed, y_train);
disp = plot_confusion_matrix(rf_balanced_solution, X_train_transformed, y_train,
                             display_labels=rf.classes_,
                             cmap=plt.cm.Blues,
                             values_format = 'd');
```



END SOLUTION

Below is the confusion matrix for the **validation** set.

In [39]:
```
disp = plot_confusion_matrix(rf, X_valid_transformed, y_valid,
                             display_labels=rf.classes_,
                             cmap=plt.cm.Blues,
                             values_format = 'd');
```



Q10

Would you say this classifier is overfit? Briefly justify your answer. **Maximum 2 sentences.**

BEGIN SOLUTION

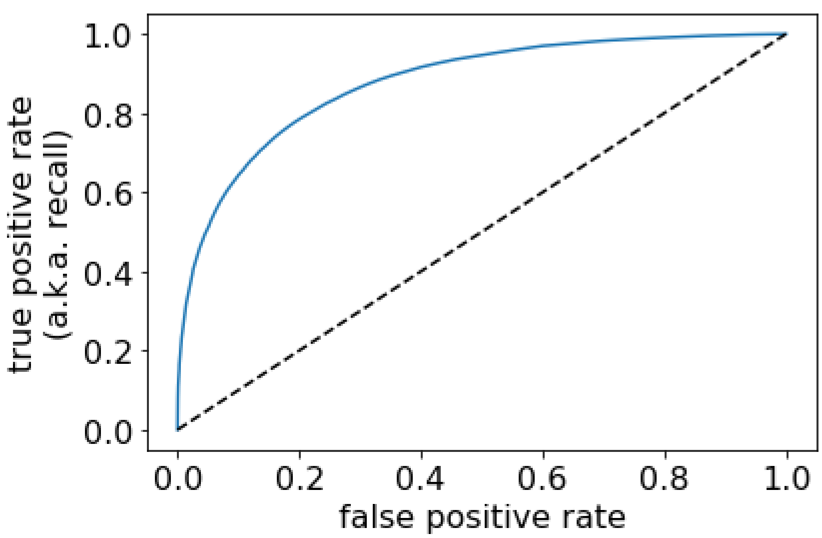
Yes, the training accuracy is extremely high, but the classifier makes lots of errors on the validation set.

END SOLUTION

In scikit-learn the `RandomForestClassifier` also has a `predict_proba` method, so we can create an ROC curve. Below I do so on the **validation** set:

In [40]:
```
fpr, tpr, thresholds = roc_curve(y_valid, rf.predict_proba(X_valid_transformed)[:,1], pos_label=

plt.plot(fpr, tpr);
plt.plot((0,1),(0,1),'--k');
plt.xlabel('false positive rate');
plt.ylabel('true positive rate\n(a.k.a. recall)');
```



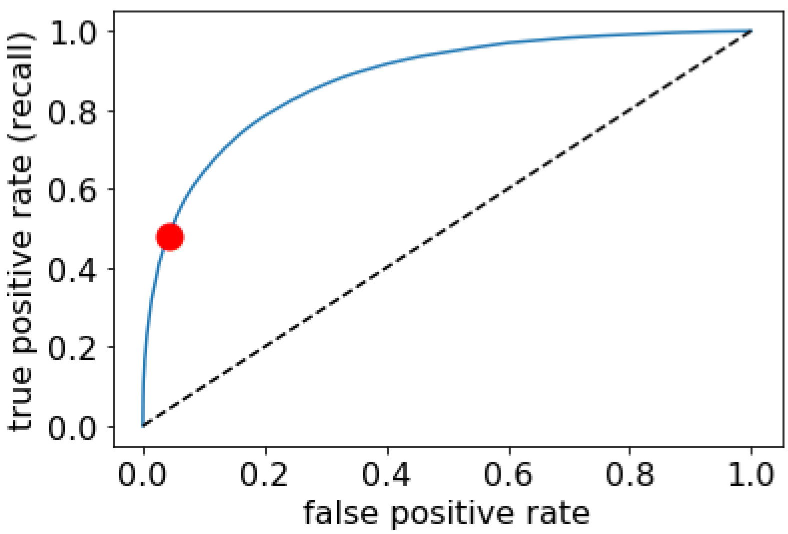
Q11

On the plot above, draw a circle to mark the point where the probability cutoff threshold is equal to 0.5. Briefly justify your answer. **Maximum 3 sentences.**

BEGIN SOLUTION

This is a tricky one! The threshold=0.5 corresponds to the behaviour of `predict`. From the above confusion matrix we can see that the recall on the validation set is equal to 5021/(5021+5648), or just below 0.5. Therefore the mark should be drawn when true positive rate (aka recall) is just below 0.5. Here it is:

In [41]:
```
plt.plot(fpr, tpr);
ind = np.argmin(np.abs(thresholds-0.5))
plt.plot(fpr[ind], tpr[ind], 'ro', markersize=13)
plt.plot((0,1),(0,1),'--k');
plt.xlabel('false positive rate');
plt.ylabel('true positive rate (recall)');
```



To confirm this:

In [42]:
```
from sklearn.metrics import confusion_matrix, recall_score
```

In [43]:
```
cm = confusion_matrix(y_valid, rf.predict(X_valid_transformed))
cm
```

Out[43]:
```
array([[38485,  1573],
       [ 5649,  5021]])
```

In [44]:
```
cm[1,1] / np.sum(cm[1])
```

Out[44]:
```
0.4705716963448922
```

END SOLUTION

The following code grabs three classifiers learned above:

- The `DummyClassifier` called `dc`.
- The `LogisticRegression` called `lr`.
- The `RandomForestClassifier` called `rf`.

In [45]:
```
some_models = [dc, lr, rf]
```

Next, I shuffle the list of models so you don't know what order they are in.

In [46]:
```
np.random.seed(999)
some_models = np.random.permutation(some_models)
```

To remind you, here is the training accuracy in each case:

In [47]:
```
dc.score(X_train_transformed, y_train)
```

Out[47]:
```
0.7669756149699959
```

In [48]:
```
lr.score(X_train_transformed, y_train)
```

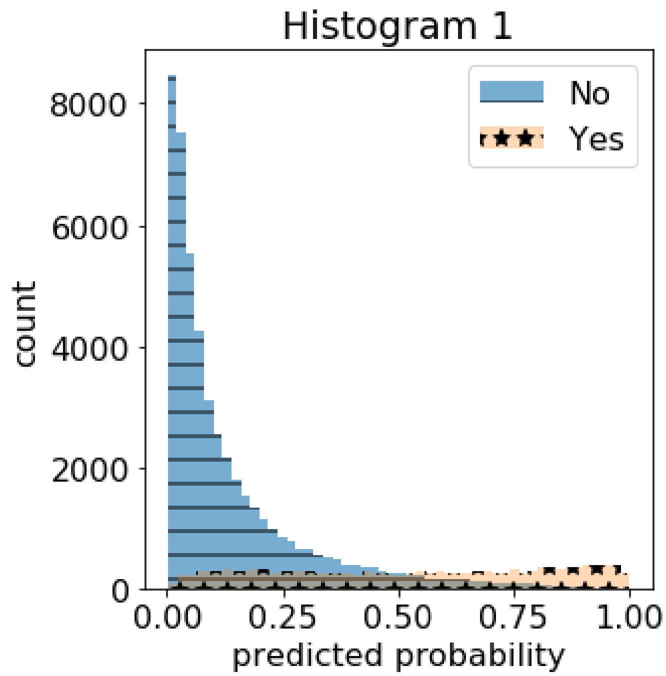
Out[48]:
```
0.8466201462796414
```

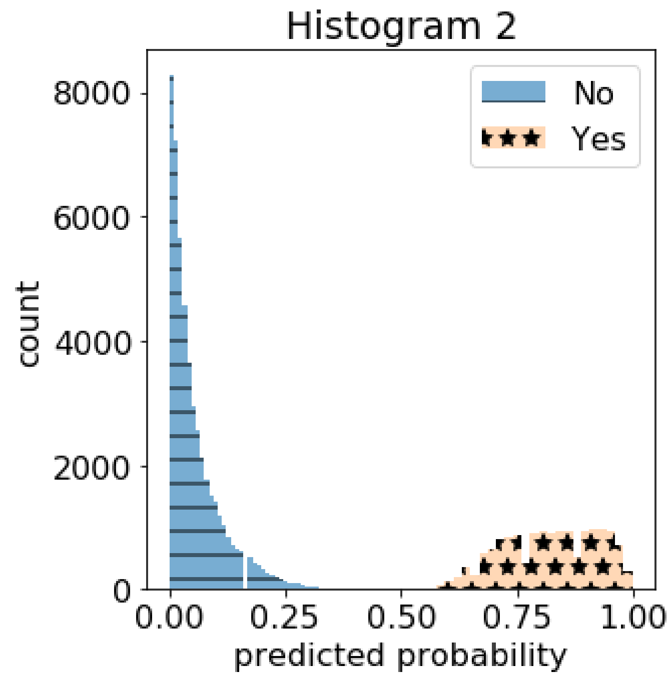
In [49]:
```
rf.score(X_train_transformed, y_train)
```

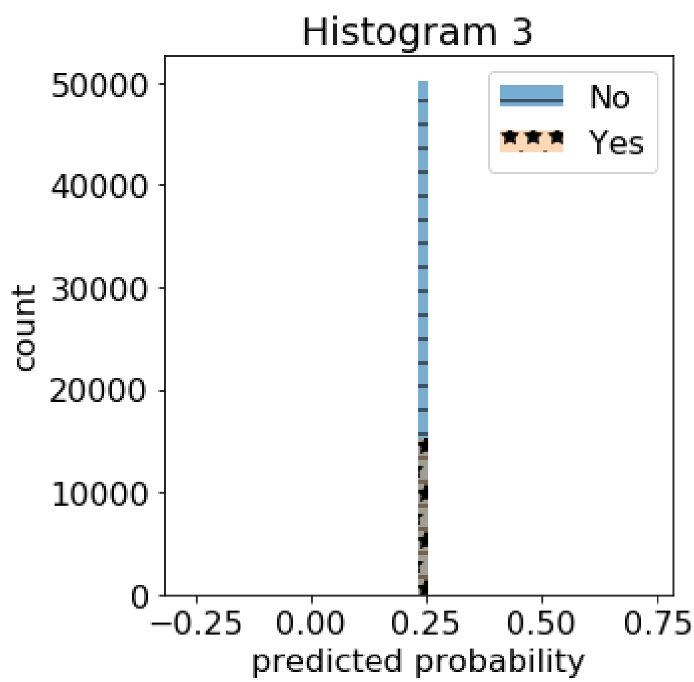
Out[49]:
```
0.9998778458108748
```

In Lecture 8 we looked at some histograms of the predicted probabilities, split by the true class. The following code creates 3 such histograms for 3 different models, using the training set.

In [69]:
```
plt.figure(figsize=(10,10))
for i, model in enumerate(some_models):
    plt.subplot(2,2,i+1)
    plt.hist(model.predict_proba(X_train_neg)[:,1], alpha=0.6, bins=50, label="No", hatch="-")
    plt.hist(model.predict_proba(X_train_pos)[:,1], alpha=0.3, bins=50, label="Yes", hatch="*")
    plt.legend(loc='upper right')
    plt.xlabel('predicted probability')
    plt.ylabel("count")
    plt.title(f"Histogram {i+1}")
plt.tight_layout();
```







Q12

I haven't told you which model is being used to generate each histogram. Which of the 3 histograms (Histogram 1, Histogram 2, or Histogram 3) do you think corresponds to the **logistic regression** (`lr`) model? Briefly justify your answer. **Maximum 3 sentences.**

BEGIN SOLUTION

The 3rd one can be identified as the `DummyClassifier` because the predicted probability is the same for every insance. Of the remaining two, the 2nd one can be identified as the `RandomForestClassifier` because it has extremely high traning accuracy. That leaves **Histogram 1** for logistic regression.

We can verify:

In [51]:
```
some_models
```

Out[51]:
```
array([LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=200,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False),
       RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=False, random_state=123,
                       verbose=0, warm_start=False),
       DummyClassifier(constant=None, random_state=None, strategy='prior')],
      dtype=object)
```

END SOLUTION

Next, I want to optimize the hyperparameters of my random forest.

In [52]:
```
param_grid = {
              "n_estimators"     : [10,100],
              "max_depth"        : [3, 5, 10, 15, None],
              "max_features"     : [3, None]
             }
param_grid
```

Out[52]:
```
{'n_estimators': [10, 100],
 'max_depth': [3, 5, 10, 15, None],
 'max_features': [3, None]}
```

In [53]:
```
grid_search = GridSearchCV(RandomForestClassifier(),
                           param_grid, cv=5, refit=False,
                           verbose=5, n_jobs=-1)
```

Q13

For the grid search above, how many models are trained in total? Briefly justify your answer. **Maximum 2 sentences.**

Note: Don't forget to account for both the different hyperparameter values and the cross-validation folds. Also, I set `refit=False` so you don't have to account for one extra model being trained at the end.

BEGIN SOLUTION

We have $2 \times 5 \times 2=20$ hyperparameter values and 5 cross_validation folds for a total of 100 trained models.

END SOLUTION

At the next point of my analysis, I experience temporary insanity. I do several crazy things:

1. I set all relevant hyperparameters to 3, because 3 is a really cool number.
2. I decide to just optimize `random_state` using `GridSearchCV`, trying all integers from 0 to 999 for the `random_state`.
3. I decide to just use the first 100 training examples for my cross-validation, because I'm too impatient to wait any longer.

In [54]:

```
grid_search = GridSearchCV(RandomForestClassifier(n_estimators=3, max_depth=3, max_features=3),
                           {"random_state" : list(range(1000))},
                           cv=3, verbose=0, n_jobs=-1)
```

In [55]:

```
grid_search.fit(X_train_transformed[:100], y_train[:100]);
```

Upon doing so, I get a fantastic cross-validation score:

In [56]:

```
grid_search.best_score_
```

Out[56]:

```
0.9402852049910874
```

I will now test out this model on the test set:

In [57]:

```
grid_search.score(X_test_transformed, y_test)
```

Out[57]:

```
0.6378301378301379
```

Q14

Explain why the test accuracy is so much worse than the cross-validation score. **Maximum 3 sentences.**

BEGIN SOLUTION

We are only optimizing `random_state` so there's no reason to expect the winning model is any better than the others. It gets a high cross-validation accuracy because we tried so many cases on such a small dataset. But the high accuracy we observe is nonsense.

END SOLUTION
