Goal

The purpose of this ML model is to take a problem description, a question, a student's answer, and whether or not the response is correct, correct, contradictory, or incorrect. **We will not be required to provide references for your answers**. They're in the application memory because it only functions in the context of prior asked questions, this repository is designed as a set of a machine learning system designed to evaluate students answers.

import libraries

In [ ]:
```
import os
import pickle

import numpy as np
from numpy.linalg import norm
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, classification_report
from pyemd import emd

from utils import get_hash
from utils import Featurizer
from utils import plot_confusion_matrix
```

I- Importing the Data

During the preparation phase, we will read modeling and test data that were prepared via a random split. 70% of the cases in the original data are represented in the training set. In order to construct features, we saved 10% to generate references (student answers that will be paired with reference answers). The remaining 20% of the original data is in the test set. We'll employ a 10-fold cross-validation approach on the training set because the data is so little.

In [2]:
```
train = pd.read_csv(os.path.join('generatedData', 'train.csv'))
print('Found %d instances in training set.' %len(train))
test = pd.read_csv(os.path.join('generatedData', 'test.csv'))
print('Found %d instances in test set.' %len(test))
```

```
Found 628 instances in training set.
Found 180 instances in test set.
```

The references are observations from the training set, which are a combination of student and reference responses. Using pre-trained word embeddings, we'll generate similarity features based on those references. During the preprocessing phase, the embeddings in the reference dataset were already computed.

In [3]:
```
references = pd.read_csv(os.path.join('generatedData', 'references.txt'), sep="\t")
references['embedding'] = references['embedding'].apply(lambda x : list(map(float, x.split(','))))
print('Found %d references.' %len(references))
references.head()
```

```
Found 318 landmarks.
```

Out[3]:

	pd_hash	qu_hash	label	answer	embedding
0	1e16b87c67	a149b85e97	0	Since the windshield exerts a force on the mos...	[0.07263770470252404, 0.05414287860576923, 0.0...
1	1e16b87c67	a149b85e97	0	The action is the windshield squashing the mo...	[0.0673675537109375, 0.05970594618055555, 0.00...
2	1e16b87c67	a149b85e97	0	The force exerted by the windshield on the mos...	[0.043080647786458336, 0.06363932291666667, 0....
3	1e16b87c67	a149b85e97	0	The force exerted by the windshield on the mos...	[0.05015497622282609, 0.07818868885869565, 0.0...
4	0c186b934b	af26c01763	0	The forces acting on the puck while it is betw...	[0.011857874253216912, 0.04596191294053022, 0....

II- Feature Engineering Phase

To begin, we'll need a featurizer to execute text activities such as constructing embeddings and computing various similarity scores between phrases. This will allow you to compare the contextual similarity of a student's answer to that of a reference answer, for example.

In [4]:
```
# Create a featurizer object that converts a phrase into embedding vector using pre-trained word2vec
emb_file = os.path.join('data', 'GoogleNews-vectors-negative300.bin')
featurizer = Featurizer(emb_file)
```

```
INFO: Loading word vectors...
INFO: Done! Using 3000000 word vectors from pre-trained word2vec.
```

Therefore, assuming an instance of a student answer to a question, we might need a function that creates some features: 1- Using the doc2vec embeddings, find cosine similarity to all references. 2- The percentage of tokens in each reference that aren't in the student response. 3- The percentage of tokens in a student's answer that aren't in any of the references 4- The number of tokens shared by the student response and each reference 5- Indicates whether or not the student's answer is context-free (zero embedding)

In [5]:
```
def get_features(references, obs):
    """"Create all features to represent an observation.

    Args:
        references (dataframe) reference instances from preprocessing
        obs : (series) one instance in train or test dataframe

    Returns:
        features : a numpy vector with float numbers
    """

    # Get observation values
    pd_hash = get_hash(obs['problem_description'])
    qu_hash = get_hash(obs['question'])
    emb = featurizer.doc2vec(obs['answer'])

    # reference of different question will get zero similarity (default)
    qu_land = references.copy()
    qu_land['similarity'] = 0 # Compute cosine similarity with reference
    qu_land['asym_diff_left'] = 0 # asymmetric difference between answer and reference
    qu_land['asym_diff_right'] = 0 # asymmetric diffence between reference and answer
    qu_land['word_match'] = 0 # word match between reference and answer
    #qu_land['wmdist'] = 0 # world mover's distance between reference and answer

    # Compute similarity when embedding is not zero and reference from same question
    if norm(emb)!=0:
        # Get index of references with same problem  and question
        idx = qu_land[(qu_land['pd_hash']==pd_hash) & (qu_land['qu_hash']==qu_hash)].index
        # Compute the direct similarity with these references
        qu_land.loc[idx, 'similarity'] = qu_land.loc[idx, 'embedding'].apply(lambda x : featurizer.cossim_from_emb(emb, np.array(x)))
        # Compute the asymmetric difference between answer and reference
        qu_land.loc[idx, 'asym_diff_left'] = qu_land.loc[idx, 'answer'].apply(lambda x : featurizer.asym_diff(obs['answer'], x))
        # Compute the asymmetric difference between reference and answer
        qu_land.loc[idx, 'asym_diff_right'] = qu_land.loc[idx, 'answer'].apply(lambda x : featurizer.asym_diff(x, obs['answer']))
        # Compute the word match ratio between answer and reference
        qu_land.loc[idx, 'word_match'] = qu_land.loc[idx, 'answer'].apply(lambda x : featurizer.word_match(obs['answer'], x))
        # Compute the world mover's distance between answer and reference
        #qu_land.loc[idx, 'wmdist'] = qu_land.loc[idx, 'answer'].apply(lambda x : featurizer.wmdist(obs['answer'], x))

    # Features will be all similarity measures to references
    features = np.concatenate((qu_land['similarity'],
                               qu_land['asym_diff_left'],
                               qu_land['asym_diff_right'],
                               qu_land['word_match']))

    # Add feature to indicate wether or not observation embedding was zero
    if norm(emb)==0:
        features = np.append(1, features)
    else:
        features = np.append(0, features)

    """# Add a feature to indicate similarity to question
    sim_to_qu = featurizer.cossim_from_phrase(obs['answer'], obs['question'])
    features = np.append(sim_to_qu, features)

    # Add a feature to indicate similarity to problem description
    sim_to_pd = featurizer.cossim_from_phrase(obs['answer'], obs['problem_description'])
    features = np.append(sim_to_pd, features)"""

    return features
```

For training and evaluation, we can now extract features from all training and test examples and obtain their labels.

In [6]:
```
# Function to featurize a dataset
def kernel_matrix(data, references):
    features = np.array(list(data.apply(lambda x : get_features(references, x), axis=1)))
    return(features)

# Prepare features
X_train = kernel_matrix(train, references)
X_test = kernel_matrix(test, references)

# Prepare labels
y_train = np.array(train['label'])
y_test = np.array(test['label'])

print('Number of features: {}'.format(X_train.shape[1]))
print('number of labels: {}'.format(np.unique(y_train).size))
```

```
Number of features: 1273
number of labels: 4
```

III- Model Training Phase

We will not apply any complex non linear models because the training set is rather tiny, as this may raise the danger of overfitting. Tree-based models such as RandomForest and Xgboost are not well-suited, especially when the number of features is large and expected to grow as more teachers and students provide reference responses. When the dataset is limited, linear models paired with kernel characteristics might produce interesting results. Then we'll use a penalized multinomial logistic regression (softmax) with a 10-fold cross-validation technique to fine-tune it.

In [9]:
```
from sklearn.model_selection import GridSearchCV
import time

print("Fitting the classifier to the training set...")
t0 = time.time()

param_grid = {'C': [1e-1, 3e-1, 1, 3, 1e1, 3e1, 1e2, 3e2]}
clf = GridSearchCV(LogisticRegression(random_state=22, solver='lbfgs', max_iter=1000, multi_class='multinomial'),
                   param_grid,
                   cv=10,
                   verbose=1,
                   n_jobs=-1)

clf = clf.fit(X_train, y_train)
model = clf.best_estimator_
if not os.path.exists('model'):
        os.makedirs('model')
pickle.dump(model, open(os.path.join('model', 'multinomial_lr.pkl'), 'wb'))

print("Training took %.3fs" %(time.time() - t0))
print("Best score on cross-validation: %.2f" %clf.best_score_)
print("Best estimator found by grid search:")
print(model)
```

```
Fitting the classifier to the training set...
Fitting 10 folds for each of 8 candidates, totalling 80 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    4.4s
[Parallel(n_jobs=-1)]: Done  80 out of  80 | elapsed:   33.4s finished
/anaconda3/lib/python3.6/site-packages/sklearn/model_selection/_search.py:841: DeprecationWarning: The default of the `iid` parameter will change f
rom True to False in version 0.22 and will be removed in 0.24. This will change numeric results when test-set sizes are unequal.
  DeprecationWarning)
Training took 33.634s
Best score on cross-validation: 0.58
Best estimator found by grid search:
LogisticRegression(C=3, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=1000, multi_class='multinomial',
          n_jobs=None, penalty='l2', random_state=22, solver='lbfgs',
          tol=0.0001, verbose=0, warm_start=False)
```

IV- Model Evaluation Phase

Now let us execute predictions on all of the test set's instances. We may compare the F1-score and the accuracy of these predictions across different classes.

In [10]:
```
model.predict(X_test)
```

Out[10]:
```
array([0, 3, 0, 0, 1, 3, 0, 1, 1, 0, 2, 0, 1, 1, 2, 3, 3, 0, 3, 1, 0, 0,
       0, 3, 3, 0, 1, 0, 1, 3, 2, 3, 3, 3, 3, 0, 0, 1, 3, 3, 3, 0, 0, 2,
       0, 3, 2, 0, 3, 0, 3, 2, 0, 0, 0, 1, 0, 3, 1, 0, 3, 0, 3, 0, 0, 0,
       0, 0, 0, 1, 3, 1, 0, 3, 1, 1, 0, 1, 0, 1, 0, 3, 0, 2, 0, 2, 0, 0,
       3, 0, 2, 3, 1, 3, 1, 0, 0, 0, 2, 0, 1, 3, 0, 2, 0, 1, 0, 0, 0, 0,
       1, 3, 1, 1, 2, 0, 0, 0, 0, 1, 3, 3, 3, 3, 3, 0, 0, 0, 2, 2, 2, 0,
       3, 2, 1, 0, 3, 0, 1, 1, 0, 0, 0, 3, 1, 0, 0, 1, 3, 0, 1, 3, 0, 0,
       0, 0, 1, 3, 1, 2, 3, 0, 3, 0, 1, 0, 3, 0, 1, 1, 1, 3, 0, 2, 0, 0,
       2, 0, 3, 0])
```

1- Accuracy

In [11]:
```
# Accuracy on training set
y_hat_train = model.predict(X_train)
acc = np.round(np.mean(y_train == y_hat_train),2)
print("Performance on training set")
print('Accuracy: {}'.format(acc))
```

```
Performance on training set
Accuracy: 0.75
```

In [12]:
```
# Accuracy on 10-fold cross-validation
print("Performance on 10-fold cross-valiation")
print('Accuracy: {}'.format(round(clf.best_score_,2)))
```

```
Performance on 10-fold cross-valiation
Accuracy: 0.58
```

In [13]:
```
# Accuracy on test set
y_hat_test = model.predict(X_test)
acc = np.round(np.mean(y_test == y_hat_test),2)
print("Performance on test set")
print('Accuracy: {}'.format(acc))
```

```
Performance on test set
Accuracy: 0.59
```

Overfitting can be seen in the training data. More data or a reduction in the amount of complicated features can be used to tackle this problem. What matters is the consistency that the cross-validation technique provides (very close performance to test set). The 10-fold cv can be used to fine-tune the model and estimate performance on final test examples.

2- Confusion Matrix

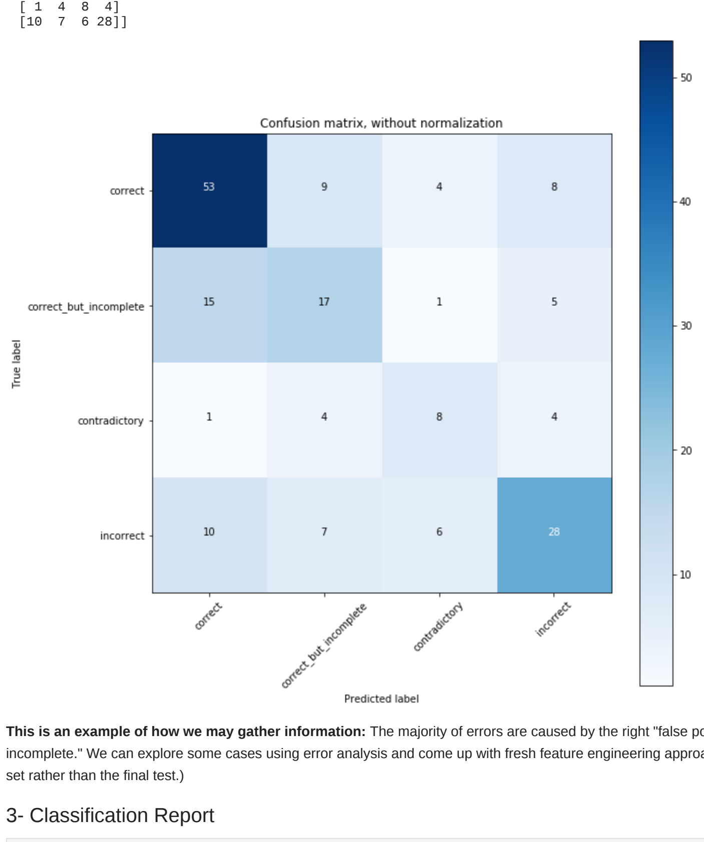
The confusion By comparing the predictions on the test set to real labels, the confusion matrix explaines the model's performance.

In [14]:
```
# Prepare class names for display
class_dict = {0:'correct', 1:'correct_but_incomplete', 2:'contradictory', 3:'incorrect'}
class_ids = list(np.unique(y_test))
class_names = [class_dict[cid] for cid in class_ids]
```

In [17]:
```
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, y_hat_test)
np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
plt.figure(figsize=(10,10))
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix, without normalization',
                      cmap=plt.cm.Blues)
```

```
Confusion matrix, without normalization
[[53  9  4  8]
 [15 17  1  5]
 [ 1  4  8  4]
 [10  7  6 28]]
```



This is an example of how we may gather information: The majority of errors are caused by the right "false positives". Many of them are labeled as "incorrect" or "correct but incomplete." We can explore some cases using error analysis and come up with fresh feature engineering approaches to improve our predictions. (This should be done on a validation set rather than the final test.)

3- Classification Report

In [18]:
```
# Compute classification report
clf_report = classification_report(y_test, y_hat_test, target_names=class_names)
print(clf_report)
```

```
                        precision    recall  f1-score   support

               correct       0.67      0.72      0.69        74
correct_but_incomplete       0.46      0.45      0.45        38
         contradictory       0.42      0.47      0.44        17
             incorrect       0.62      0.55      0.58        51

             micro avg       0.59      0.59      0.59       180
             macro avg       0.54      0.55      0.54       180
          weighted avg       0.59      0.59      0.59       180
```

If we need to improve the F-score on the minority classes ("contradictory" and "correct but incomplete"), we can use manual error analysis.

V- Optional (Build a conservative system)

The model, in fact, generates probabilistic values for each class. However, even if the probability of confidence is low, the prediction comes from the class with the highest probability of confidence. When this likelihood falls below a specific level, we can imagine a system that says "I don't know." It can improve the accuracy of predictions and inspire teachers to label additional data, which will improve the ML system's training.

Let's examine how the system reacts if we change the decision threshold for whether or not to send the forecast.

In [20]:
```
def get_prediction(X, thresh):
    """"Generate class predictions with 99 indicating unknown class."""

    pred = model.predict_proba(X)
    pred = [[(class_id, proba) for (class_id, proba) in enumerate(p) if proba == np.max(p)] for p in pred]
    pred = [p[0][0] if p[0][1]>thresh else 99 for p in pred]
    return np.array(pred)

def get_performance(predictions, labels, thresh):
    """Measure the accuracy and the unknown rate depending on the threshold

    Args:
        predictions: np.array of class predictions
        label: list of labels
        thresh: distance threshold above which the prediction becomes unknown

    Returns:
        accuracy: proportion of correct predictions when not unkown
        unknown_rate: proportion of predictions that are unknown
    """

    # Measure the rate of known predictions
    response_rate = 1 - np.mean(predictions==99)

    # Get the indices of predictions to keep
    known_idx = [i for i in range(len(predictions)) if predictions[i]!=99]

    # get predictions that are not unknown
    mini_predictions = np.array([predictions[idx] for idx in known_idx])
    mini_labels = np.array([labels[idx] for idx in known_idx])

    # Measure the accuracy
    accuracy = np.mean(mini_predictions == mini_labels)

    # Ouput dictionary
    output = {'accuracy': accuracy,
              'response_rate': response_rate}

    return output


# Plot the performance against the threshold
accuracy = []
response_rate = []
threshold = np.linspace(start = 0, stop = 1, num=100)

for thresh in threshold:
    predictions = get_prediction(X_test, thresh)
    labels = y_test
    perf = get_performance(predictions, labels, thresh)
    accuracy.append(perf['accuracy'])
    response_rate.append(perf['response_rate'])

plt.figure(figsize=(15,6))
plt.plot(threshold, response_rate)
plt.plot(threshold, accuracy)
plt.legend(['response_rate', 'accuracy'], loc='lower right')
plt.title('Accuracy vs Response rate')
plt.xlabel('Threshold')
plt.grid(True)
plt.show()
```

```
/anaconda3/lib/python3.6/site-packages/numpy/core/fromnumeric.py:3118: RuntimeWarning: Mean of empty slice.
  out=out, **kwargs)
/anaconda3/lib/python3.6/site-packages/numpy/core/_methods.py:85: RuntimeWarning: invalid value encountered in double_scalars
  ret = ret.dtype.type(ret / rcount)
```


With a higher decision threshold, accuracy could climb to 90%, but the system's response rate will drop to 30%.

In [ ]: