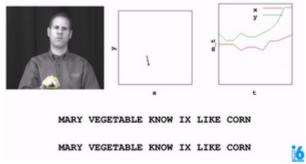
# **Artificial Intelligence Engineer Nanodegree - Probabilistic Models**

## **Project: Sign Language Recognition System**

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## Introduction

The overall goal of this project is to build a word recognizer for American Sign Language video sequences, demonstrating the power of probabalistic models. In particular, this project employs <a href="https://en.wikipedia.org/wiki/Hidden\_Markov\_model">https://en.wikipedia.org/wiki/Hidden\_Markov\_model</a>) to analyze a series of measurements taken from videos of American Sign Language (ASL) collected for research (see the <a href="https://www-i6.informatik.rwth-aachen.de/~dreuw/database-rwth-boston-104.php">https://www-i6.informatik.rwth-aachen.de/~dreuw/database-rwth-boston-104.php</a>)). In this video, the right-hand x and y locations are plotted as the speaker signs the sentence.



(https://drive.google.com/open?id=0B 5gGuFe-wbhUXRuVnNZVnMtam8)

The raw data, train, and test sets are pre-defined. You will derive a variety of feature sets (explored in Part 1), as well as implement three different model selection criterion to determine the optimal number of hidden states for each word model (explored in Part 2). Finally, in Part 3 you will implement the recognizer and compare the effects the different combinations of feature sets and model selection criteria.

At the end of each Part, complete the submission cells with implementations, answer all questions, and pass the unit tests. Then submit the completed notebook for review!

## **PART 1: Data**

## **Features Tutorial**

## Load the initial database

A data handler designed for this database is provided in the student codebase as the As1Db class in the as1\_data module. This handler creates the initial pandas (http://pandas.pydata.org/pandas-docs/stable/) dataframe from the corpus of data included in the data directory as well as dictionaries suitable for extracting data in a format friendly to the <a href="https://hmmlearn.readthedocs.io/en/latest/">hmmlearn (https://hmmlearn.readthedocs.io/en/latest/</a>) library. We'll use those to create models in Part 2.

To start, let's set up the initial database and select an example set of features for the training set. At the end of Part 1, you will create additional feature sets for experimentation.

In [1]: import numpy as np
 import pandas as pd
 from asl\_data import AslDb

asl = AslDb() # initializes the database asl.df.head() # displays the first five rows of the asl database, indexed by v ideo and frame

## Out[1]:

		left-x	left-y	right-x	right-y	nose-x	nose-y	speaker	
video	frame								
	0	149	181	170	175	161	62	woman-1	
	1	149	181	170	175	161	62	woman-1	
98	2	149	181	170	175	161	62	woman-1	
	3	149	181	170	175	161	62	woman-1	
	4	149	181	170	175	161	62	woman-1	

In [2]: asl.df.ix[98,1] # look at the data available for an individual frame

Out[2]: left-x 149
 left-y 181
 right-x 170
 right-y 175
 nose-x 161
 nose-y 62
 speaker woman-1

Name: (98, 1), dtype: object

The frame represented by video 98, frame 1 is shown here:



## Feature selection for training the model

The objective of feature selection when training a model is to choose the most relevant variables while keeping the model as simple as possible, thus reducing training time. We can use the raw features already provided or derive our own and add columns to the pandas dataframe asl.df for selection. As an example, in the next cell a feature named 'grnd-ry' is added. This feature is the difference between the right-hand y value and the nose y value, which serves as the "ground" right y value.

Out	[3]	١:

		left-x	left-y	right-x	right-y	nose-x	nose-y	speaker	grnd-ry
video	frame								
	0	149	181	170	175	161	62	woman-1	113
	1	149	181	170	175	161	62	woman-1	113
98	2	149	181	170	175	161	62	woman-1	113
	3	149	181	170	175	161	62	woman-1	113
	4	149	181	170	175	161	62	woman-1	113

Try it!

asl.df sample

		left- x	left- y	right- x	right- y	nose-	nose-	speaker	grnd- ry	grnd- rx	grnd- ly	grnd-
video	frame											
	0	149	181	170	175	161	62	woman-	113	9	119	-12
	1	149	181	170	175	161	62	woman-	113	9	119	-12
98	2	149	181	170	175	161	62	woman-	113	9	119	-12
	3	149	181	170	175	161	62	woman-	113	9	119	-12
	4	149	181	170	175	161	62	woman-	113	9	119	-12

Out[4]: Correct!

```
In [5]: # collect the features into a list
    features_ground = ['grnd-rx','grnd-ry','grnd-lx','grnd-ly']
    #show a single set of features for a given (video, frame) tuple
    [asl.df.ix[98,1][v] for v in features_ground]
```

Out[5]: [9, 113, -12, 119]

## Build the training set

Now that we have a feature list defined, we can pass that list to the build\_training method to collect the features for all the words in the training set. Each word in the training set has multiple examples from various videos. Below we can see the unique words that have been loaded into the training set:

```
In [6]: training = asl.build_training(features_ground)
    print("Training words: {}".format(training.words))
```

Training words: ['JOHN', 'WRITE', 'HOMEWORK', 'IX-1P', 'SEE', 'YESTERDAY', 'IX', 'LOVE', 'MARY', 'CAN', 'GO', 'GO1', 'FUTURE', 'GO2', 'PARTY', 'FUTURE1', 'HIT', 'BLAME', 'FRED', 'FISH', 'WONT', 'EAT', 'BUT', 'CHICKEN', 'VEGETABL E', 'CHINA', 'PEOPLE', 'PREFER', 'BROCCOLI', 'LIKE', 'LEAVE', 'SAY', 'BUY', 'HOUSE', 'KNOW', 'CORN', 'CORN1', 'THINK', 'NOT', 'PAST', 'LIVE', 'CHICAGO', 'CAR', 'SHOULD', 'DECIDE', 'VISIT', 'MOVIE', 'WANT', 'SELL', 'TOMORROW', 'NEX T-WEEK', 'NEW-YORK', 'LAST-WEEK', 'WILL', 'FINISH', 'ANN', 'READ', 'BOOK', 'CHOCOLATE', 'FIND', 'SOMETHING-ONE', 'POSS', 'BROTHER', 'ARRIVE', 'HERE', 'GIV E', 'MAN', 'NEW', 'COAT', 'WOMAN', 'GIVE1', 'HAVE', 'FRANK', 'BREAK-DOWN', 'SEARCH-FOR', 'WHO', 'WHAT', 'LEG', 'FRIEND', 'CANDY', 'BLUE', 'SUE', 'BUY1', 'STOLEN', 'OLD', 'STUDENT', 'VIDEOTAPE', 'BORROW', 'MOTHER', 'POTATO', 'TEL L', 'BILL', 'THROW', 'APPLE', 'NAME', 'SHOOT', 'SAY-1P', 'SELF', 'GROUP', 'JA NA', 'TOY1', 'MANY', 'TOY', 'ALL', 'BOY', 'TEACHER', 'GIRL', 'BOX', 'GIVE2', 'GIVE3', 'GET', 'PUTASIDE']

The training data in training is an object of class WordsData defined in the asl\_data module. in addition to the words list, data can be accessed with the get\_all\_sequences, get\_all\_Xlengths, get\_word\_sequences, and get\_word\_Xlengths methods. We need the get\_word\_Xlengths method to train multiple sequences with the hmmlearn library. In the following example, notice that there are two lists; the first is a concatenation of all the sequences(the X portion) and the second is a list of the sequence lengths(the Lengths portion).

```
In [7]: training.get_word_Xlengths('CHOCOLATE')
Out[7]: (array([[-11,
                          48,
                                  7, 120],
                          48,
                                  8, 109],
                   [-11,
                    -8,
                          49,
                                11,
                                      98],
                     -7,
                          50,
                                 7,
                                      87],
                           54,
                     -4,
                                 7,
                                      77],
                     -4,
                           54,
                                  6,
                                      69],
                           54,
                    -4,
                                  6,
                                      69],
                   [-13,
                           52,
                                  6,
                                      69],
                   [-13,
                          52,
                                 6,
                                      69],
                                      69],
                    -8,
                           51,
                                  6,
                     -8,
                           51,
                                  6,
                                      69],
                    -8,
                          51,
                                      69],
                                  6,
                    -8,
                           51,
                                  6,
                                      69],
                    -8,
                          51,
                                 6,
                                      69],
                           59,
                                  7,
                   [-10,
                                      71],
                   [-15]
                          64,
                                 9,
                                      77],
                          75,
                   [-17,
                                13,
                                      81],
                     -4,
                          48,
                                -4, 113],
                     -2,
                           53,
                                -4, 113],
                     -4,
                           55,
                                  2,
                                      98],
                                      98],
                     -4,
                           58,
                                  2,
                     -1,
                           59,
                                  2,
                                      89],
                           59,
                                      84],
                     -1,
                                -1,
                     -1,
                           59,
                                -1,
                                      84],
                     -7,
                          63,
                                -1,
                                      84],
                     -7,
                          63,
                                -1,
                                      84],
                     -7,
                                  3,
                          63,
                                      83],
                     -7,
                          63,
                                      83],
                                  3,
                     -7,
                          63,
                                      83],
                                  3,
                     -7,
                          63,
                                  3,
                                      83],
                     -7,
                          63,
                                  3,
                                      83],
                     -7,
                          63,
                                  3,
                                      83],
                     -7,
                                      83],
                          63,
                                  3,
                                      83],
                     -4,
                          70,
                                  3,
                     -4,
                          70,
                                 3,
                                      83],
                          73,
                     -2,
                                  5,
                                      90],
                                      96],
                     -3,
                          79,
                                -4,
                   [-15,
                          98,
                                13, 135],
                     -6,
                          93,
                                12, 128],
                          89,
                                14, 118],
                     -2,
                      5,
                          90,
                                10, 108],
                      4,
                          86,
                                 7, 105],
                                 7, 105],
                      4,
                          86,
                      4,
                          86,
                                13, 100],
                     -3,
                          82,
                                14,
                                      96],
                                      96],
                     -3,
                          82,
                                14,
                      6,
                          89,
                                16, 100],
                          89,
                      6,
                                16, 100],
                      7,
                          85,
                                17, 111]], dtype=int64), [17, 20, 12])
```

#### More feature sets

So far we have a simple feature set that is enough to get started modeling. However, we might get better results if we manipulate the raw values a bit more, so we will go ahead and set up some other options now for experimentation later. For example, we could normalize each speaker's range of motion with grouped statistics using Pandas stats (http://pandas.pydata.org/pandas-docs/stable/api.html#api-dataframe-stats) functions and pandas groupby (http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.groupby.html). Below is an example for finding the means of all speaker subgroups.

Out[8]:

	left-x	left-y	right-x	right-y	nose-x	nose-y	grnd-ry
speaker							
man-1	206.248203	218.679449	155.464350	150.371031	175.031756	61.642600	88.7284
woman-	164.661438	161.271242	151.017865	117.332462	162.655120	57.245098	60.0873
woman-	183.214509	176.527232	156.866295	119.835714	170.318973	58.022098	61.8136

To select a mean that matches by speaker, use the pandas <u>map (http://pandas.pydata.org/pandas.docs/stable/generated/pandas.Series.map.html)</u> method:

Out[9]:

		left- x	left- y	right- x	right- y	nose-	nose- y	speaker	grnd- ry	grnd- rx	grnd- ly	grnd- lx	le m
video	frame												
	0	149	181	170	175	161	62	woman-	113	9	119	-12	1(
	1	149	181	170	175	161	62	woman-	113	9	119	-12	1(
98	2	149	181	170	175	161	62	woman-	113	9	119	-12	1(
	3	149	181	170	175	161	62	woman-	113	9	119	-12	1(
	4	149	181	170	175	161	62	woman-	113	9	119	-12	1(

```
In [10]: from asl_utils import test_std_tryit
    # TODO Create a dataframe named `df_std` with standard deviations grouped by s
    peaker
    df_std = asl.df.groupby('speaker').std()
    #asl.df['df_std']= asl.df['speaker'].map(df_std['left-x'])

# test the code
    test_std_tryit(df_std)
```

df\_std

	left-x	left-y	right-x	right-y	nose-x	nose-y	grnd-ry	grn
speaker								
man-1	15.154425	36.328485	18.901917	54.902340	6.654573	5.520045	53.487999	20.2
woman-	17.573442	26.594521	16.459943	34.667787	3.549392	3.538330	33.972660	16.
woman-	15.388711	28.825025	14.890288	39.649111	4.099760	3.416167	39.128572	16. <sup>-</sup>

Out[10]: Correct!

.

## **Features Implementation Submission**

Implement four feature sets and answer the question that follows.

- normalized Cartesian coordinates
  - use mean and standard deviation statistics and the <u>standard score</u> (<a href="https://en.wikipedia.org/wiki/Standard\_score">https://en.wikipedia.org/wiki/Standard\_score</a>) equation to account for speakers with different heights and arm length
- polar coordinates
  - calculate polar coordinates with <u>Cartesian to polar equations</u>
     (<a href="https://en.wikipedia.org/wiki/Polar\_coordinate\_system#Converting\_between\_polar\_and\_Cartesian\_coordinate\_system#Converting\_
  - use the np.arctan2 (https://docs.scipy.org/doc/numpy-1.10.0/reference/generated/numpy.arctan2.html) function and swap the x and y axes to move the 0 to  $2\pi$  discontinuity to 12 o'clock instead of 3 o'clock; in other words, the normal break in radians value from 0 to  $2\pi$  occurs directly to the left of the speaker's nose, which may be in the signing area and interfere with results. By swapping the x and y axes, that discontinuity move to directly above the speaker's head, an area not generally used in signing.
- · delta difference
  - as described in Thad's lecture, use the difference in values between one frame and the next frames as features
  - pandas <u>diff method (http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.diff.html)</u> and <u>fillna method</u>
     (http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.fillna.html)</u> will be helpful for this one
- · custom features
  - These are your own design; combine techniques used above or come up with something else entirely. We look forward to seeing what you come up with! Some ideas to get you started:
    - normalize using a <u>feature scaling equation</u> (<u>https://en.wikipedia.org/wiki/Feature\_scaling</u>)
    - o normalize the polar coordinates
    - adding additional deltas

```
In [11]: # TODO add features for normalized by speaker values of left, right, x, y
         # Name these 'norm-rx', 'norm-ry', 'norm-lx', and 'norm-ly'
         # using Z-score scaling (X-Xmean)/Xstd
         #asl.df['left-x-mean']= asl.df['speaker'].map(df_means['left-x']) # already do
         ne above
         asl.df['left-x-std']= asl.df['speaker'].map(df_std['left-x'])
         asl.df['norm-lx']= (asl.df['left-x'] - asl.df['left-x-mean']) / asl.df['left-x
         -std']
         asl.df['left-y-mean']= asl.df['speaker'].map(df means['left-y'])
         asl.df['left-y-std']= asl.df['speaker'].map(df_std['left-y'])
         asl.df['norm-ly']= (asl.df['left-y'] - asl.df['left-y-mean']) / asl.df['left-y
         -std']
         asl.df['right-x-mean']= asl.df['speaker'].map(df_means['right-x'])
         asl.df['right-x-std']= asl.df['speaker'].map(df_std['right-x'])
         asl.df['norm-rx']= (asl.df['right-x'] - asl.df['right-x-mean']) / asl.df['righ
         t-x-std']
         asl.df['right-y-mean']= asl.df['speaker'].map(df_means['right-y'])
         asl.df['right-y-std']= asl.df['speaker'].map(df_std['right-y'])
         asl.df['norm-ry']= (asl.df['right-y'] - asl.df['right-y-mean']) / asl.df['righ
         t-y-std']
         features norm = ['norm-rx', 'norm-ry', 'norm-lx', 'norm-ly']
In [12]: # TODO add features for polar coordinate values where the nose is the origin
         # Name these 'polar-rr', 'polar-rtheta', 'polar-lr', and 'polar-ltheta'
         # Note that 'polar-rr' and 'polar-rtheta' refer to the radius and angle
         asl.df['polar-rr']= np.sqrt(asl.df['grnd-rx']**2 + asl.df['grnd-ry']**2)
         asl.df['polar-rtheta']=np.arctan2(asl.df['grnd-rx'],asl.df['grnd-ry'])
         asl.df['polar-lr'] = np.sqrt(asl.df['grnd-lx']**2 + asl.df['grnd-ly']**2)
         asl.df['polar-ltheta']=np.arctan2(asl.df['grnd-lx'],asl.df['grnd-ly'])
         features polar = ['polar-rr', 'polar-rtheta', 'polar-lr', 'polar-ltheta']
In [13]:
         # TODO add features for left, right, x, y differences by one time step, i.e. t
         he "delta" values discussed in the lecture
         # Name these 'delta-rx', 'delta-ry', 'delta-lx', and 'delta-ly'
         asl.df['delta-rx']=asl.df['right-x'].diff().fillna(value=0)
         asl.df['delta-ry']=asl.df['right-y'].diff().fillna(value=0)
         asl.df['delta-lx']=asl.df['left-x'].diff().fillna(value=0)
         asl.df['delta-ly']=asl.df['left-y'].diff().fillna(value=0)
         features_delta = ['delta-rx', 'delta-ry', 'delta-lx', 'delta-ly']
```

```
In [14]: # TODO add features of your own design, which may be a combination of the abov
         e or something else
         # Name these whatever you would like
         # TODO define a list named 'features custom' for building the training set
         #distance from left to right hand, uses the normalized values
         asl.df['dist-norm-left-right']=np.sqrt((asl.df['norm-rx'] - asl.df['norm-
         lx'])**2+(asl.df['norm-ry'] - asl.df['norm-ly'])**2)
         #change in dist from left to right hand
         asl.df['delta-dist-norm-left-right']=asl.df['dist-norm-left-right'].diff().fil
         lna(value=0)
         features hand dist=['dist-norm-left-right','delta-dist-norm-left-right']
         #deltas of the normalized hand positions
         asl.df['delta-norm-rx'] = asl.df['norm-rx'].diff().fillna(value=0)
         asl.df['delta-norm-ry'] = asl.df['norm-ry'].diff().fillna(value=0)
         asl.df['delta-norm-lx'] = asl.df['norm-lx'].diff().fillna(value=0)
         asl.df['delta-norm-ly'] = asl.df['norm-ly'].diff().fillna(value=0)
         features_delta_norm_hand_pos=['delta-norm-rx', 'delta-norm-ry', 'delta-norm-l
         x', 'delta-norm-ly']
         #normalized polar coords:
         asl.df['norm-polar-rr'] = (asl.df['polar-rr'] - min(asl.df['polar-
         rr']))/(max(asl.df['polar-rr'])-min(asl.df['polar-rr']))
         asl.df['norm-rtheta'] = (asl.df['polar-rtheta'] - min(asl.df['polar-
         rtheta']))/(max(asl.df['polar-rtheta'])-min(asl.df['polar-rtheta']))
         asl.df['norm-polar-lr'] = (asl.df['polar-lr'] - min(asl.df['polar-
         lr']))/(max(asl.df['polar-lr'])-min(asl.df['polar-lr']))
         asl.df['norm-polar-ltheta'] = (asl.df['polar-ltheta'] - min(asl.df['polar-lthe
         ta']))/(max(asl.df['polar-ltheta'])-min(asl.df['polar-rr']))
         #delta of norm polar coords:
         asl.df['delta-norm-polar-rr'] = asl.df['norm-polar-rr'].diff().fillna(value=0)
         asl.df['delta-norm-rtheta'] = asl.df['norm-rtheta'].diff().fillna(value=0)
         asl.df['delta-norm-polar-lr'] = asl.df['norm-polar-lr'].diff().fillna(value=0)
         asl.df['delta-norm-polar-ltheta'] = asl.df['norm-polar-
         ltheta'].diff().fillna(value=0)
         features_norm_polar_coords=['norm-polar-rr','norm-rtheta','norm-polar-lr','nor
         m-polar-ltheta','delta-norm-polar-rr','delta-norm-rtheta','delta-norm-polar-l
         r', 'delta-norm-polar-ltheta']
         features custom=features hand dist+features delta norm hand pos+features norm
         polar_coords
         asl.df.tail()
```

			left-	left-	right-	right- y	nose-	nose-	speaker	grnd- ry	grnd- rx	grnd- ly	 delta norm lx
,	video	frame											
		52	148	181	171	156	162	60	woman-	96	9	121	 0.0
		53	148	181	172	165	162	60	woman-	105	10	121	 0.0
,	125	54	148	181	175	173	162	60	woman-	113	13	121	 0.0
		55	148	181	175	173	162	60	woman-	113	13	121	 0.0
		56	148	181	175	173	162	60	woman-	113	13	121	 0.0

5 rows × 45 columns

Out[14]:

```
In [15]: #list of the features
    features_ground
    features_norm
    features_polar
    features_delta
    features_custom=features_hand_dist+features_delta_norm_hand_pos+features_norm_
    polar_coords
    features_best=features_norm+features_custom
```

Question 1: What custom features did you choose for the features custom set and why?

- 1. Normalized distance from right to left hand and the delta of normalized distance between hands. The distance between hands may be an indicator, and the normalized value is preferred to assist in eliminating differences between speakers. in addition the speed/direction of moving together or apart may be an indicator.
- 2. Delta of the normalized hand position. The change in position should be based on normalized positions
- 3. Normalized Polar co-ordinates, again, to assist w/speaker independance
- 4. The related delta of the normalized Polar coords, as change in position may be helpful

## **Features Unit Testing**

Run the following unit tests as a sanity check on the defined "ground", "norm", "polar", and 'delta" feature sets. The test simply looks for some valid values but is not exhaustive. However, the project should not be submitted if these tests don't pass.

```
In [16]:
         import unittest
         # import numpy as np
         class TestFeatures(unittest.TestCase):
             def test_features_ground(self):
                  sample = (asl.df.ix[98, 1][features ground]).tolist()
                  self.assertEqual(sample, [9, 113, -12, 119])
             def test_features_norm(self):
                  sample = (asl.df.ix[98, 1][features norm]).tolist()
                  np.testing.assert_almost_equal(sample, [ 1.153,  1.663, -0.891,
         0.742], 3)
             def test features polar(self):
                  sample = (asl.df.ix[98,1][features_polar]).tolist()
                  np.testing.assert almost equal(sample, [113.3578, 0.0794, 119.603, -0.
         1005], 3)
             def test features delta(self):
                  sample = (asl.df.ix[98, 0][features delta]).tolist()
                  self.assertEqual(sample, [0, 0, 0, 0])
                  sample = (asl.df.ix[98, 18][features delta]).tolist()
                  self.assertTrue(sample in [[-16, -5, -2, 4], [-14, -9, 0, 0]], "Sample
          value found was {}".format(sample))
         suite = unittest.TestLoader().loadTestsFromModule(TestFeatures())
         unittest.TextTestRunner().run(suite)
         Ran 4 tests in 0.026s
         OK
```

## **PART 2: Model Selection**

### **Model Selection Tutorial**

The objective of Model Selection is to tune the number of states for each word HMM prior to testing on unseen data. In this section you will explore three methods:

Out[16]: <unittest.runner.TextTestResult run=4 errors=0 failures=0>

- Log likelihood using cross-validation folds (CV)
- Bayesian Information Criterion (BIC)
- Discriminative Information Criterion (DIC)

#### Train a single word

Now that we have built a training set with sequence data, we can "train" models for each word. As a simple starting example, we train a single word using Gaussian hidden Markov models (HMM). By using the fit method during training, the Baum-Welch Expectation-Maximization

(https://en.wikipedia.org/wiki/Baum%E2%80%93Welch\_algorithm) (EM) algorithm is invoked iteratively to find the best estimate for the model for the number of hidden states specified from a group of sample seequences. For this example, we assume the correct number of hidden states is 3, but that is just a guess. How do we know what the "best" number of states for training is? We will need to find some model selection technique to choose the best parameter.

```
In [17]:
         import warnings
         from hmmlearn.hmm import GaussianHMM
         def train_a_word(word, num_hidden_states, features):
             warnings.filterwarnings("ignore", category=DeprecationWarning)
             training = asl.build_training(features)
             X, lengths = training.get word Xlengths(word)
             model = GaussianHMM(n components=num hidden states, n iter=1000).fit(X, le
         ngths)
             logL = model.score(X, lengths)
             return model, logL
         demoword = 'BOOK'
         model, logL = train a word(demoword, 3, features ground)
         print("Number of states trained in model for {} is {}".format(demoword,
         model.n components))
         print("logL = {}".format(logL))
         Number of states trained in model for BOOK is 3
```

The HMM model has been trained and information can be pulled from the model, including means and variances for each feature and hidden state. The <u>log likelihood (http://math.stackexchange.com/questions/892832/why-we-consider-log-likelihood-instead-of-likelihood-in-gaussian-distribution)</u> for any individual sample or group of samples can also be calculated with the score method.

logL = -2331.113812743319

```
In [18]: def show model stats(word, model):
             print("Number of states trained in model for {} is {}".format(word,
         model.n components))
             variance=np.array([np.diag(model.covars [i]) for i in range(model.n compon
         ents)])
             for i in range(model.n_components): # for each hidden state
                 print("hidden state #{}".format(i))
                 print("mean = ", model.means_[i])
                 print("variance = ", variance[i])
                 print()
         show_model_stats(demoword, model)
         Number of states trained in model for BOOK is 3
         hidden state #0
         mean = [ -3.46504869 50.66686933 14.02391587 52.04731066]
         variance = [ 49.12346305 43.04799144 39.35109609 47.24195772]
         hidden state #1
         mean = [ -11.45300909 94.109178 19.03512475 102.2030162 ]
         variance = [ 77.403668 203.35441965 26.68898447 156.12444034]
         hidden state #2
         mean = [ -1.12415027 69.44164191 17.02866283 77.7231196 ]
         variance = [ 19.70434594    16.83041492    30.51552305    11.03678246]
```

## Try it!

Experiment by changing the feature set, word, and/or num\_hidden\_states values in the next cell to see changes in values.

```
In [19]: | my_testword = 'CHOCOLATE'
         model, logL = train_a_word(my_testword, 3, features_ground) # Experiment here
          with different parameters
         show model stats(my testword, model)
         print("logL = {}".format(logL))
         Number of states trained in model for CHOCOLATE is 3
         hidden state #0
         mean = [ 0.58333333 87.91666667 12.75
                                                            108.5
         variance = [ 39.41055556 18.74388889 9.855
                                                                144.4175
                                                                            1
         hidden state #1
         mean = \begin{bmatrix} -9.30211403 & 55.32333876 & 6.92259936 & 71.24057775 \end{bmatrix}
         variance = [ 16.16920957 46.50917372 3.81388185 15.79446427]
         hidden state #2
         mean = [ -5.40587658 60.1652424 2.32479599 91.3095432 ]
         variance = [ 7.95073876 64.13103127 13.68077479 129.5912395 ]
         logL = -601.3291470028621
```

```
In [20]: my testword = 'CHOCOLATE'
        model, logL = train_a_word(my_testword, 4, features_ground) # Experiment here
         with different parameters
        show_model_stats(my_testword, model)
        print("logL = {}".format(logL))
        Number of states trained in model for CHOCOLATE is 4
        hidden state #0
        mean = [ 0.58333258 87.91666611 12.75000001 108.49999882]
                                                9.85499958 144.41752618]
        variance = [ 39.4105671 18.74389523
        hidden state #1
        mean = [ -4.93681705 64.73171915 1.62598519 84.91459657]
        variance = [ 6.1617479 28.36616959 5.47102461 13.11696032]
        hidden state #2
        mean = [ -6.37712306 51.09867416 3.64009161 104.46268173]
        variance = [ 10.28220014 12.44316166 27.33390004 106.91029392]
        hidden state #3
        mean = [ -9.23835975 55.307463 6.92298661 71.30538347]
        variance = [ 16.30887738 45.97071639 3.76856896 15.98215464]
        logL = -565.1243334331189
In [21]: my testword = 'CHOCOLATE'
        model, logL = train_a_word(my_testword, 4, features_norm) # Experiment here wi
        th different parameters
        show model stats(my testword, model)
        print("logL = {}".format(logL))
        Number of states trained in model for CHOCOLATE is 4
        hidden state #0
        mean = [ 0.47581504 -0.25534057 -0.32768595 -1.7243523 ]
        hidden state #1
        mean = [ 0.49163141 -0.34766944 -0.19907141 -0.31200148]
        variance = [ 0.02973162  0.00401851  0.00934483  0.2921408 ]
        hidden state #2
        mean = [ 0.9894402 -0.16006052 -1.31412901 -1.55560526]
        variance = [ 0.10711401  0.00555855  0.03518414  0.09325342]
        hidden state #3
        variance = [ 0.05344461  0.02787475  0.01792018  0.07558914]
        logL = 85.72111948347856
```

```
In [22]: my testword = 'CHOCOLATE'
         model, logL = train_a_word(my_testword, 4, features_hand_dist) # Experiment he
         re with different parameters
         show_model_stats(my_testword, model)
         print("logL = {}".format(logL))
         Number of states trained in model for CHOCOLATE is 4
         hidden state #0
         mean = [0.70326771 0.00393284]
         variance = [ 0.05846787 0.12020401]
         hidden state #1
         mean = [ 1.67115958 0.08294104]
         variance = [ 0.01077021  0.05687346]
         hidden state #2
         mean = [ 2.79182418  0.08961714]
         variance = [ 0.09747049 0.09519826]
         hidden state #3
         mean = [ 1.01845213 0.02174606]
         variance = [ 0.01126724 0.01299081]
         logL = 17.011107817911498
In [23]: my testword = 'CHOCOLATE'
         model, logL = train_a_word(my_testword, 4, features_delta_norm_hand_pos) # Exp
         eriment here with different parameters
         show model stats(my testword, model)
         print("logL = {}".format(logL))
         Number of states trained in model for CHOCOLATE is 4
         hidden state #0
         mean = [-0.0480411  0.02301395  0.33806905 -0.28418428]
         variance = [ 0.00750924  0.00480335  0.00794685  0.05676355]
         hidden state #1
         mean = [-0.05712648 0.09690884 0.02703457 0.09635826]
         variance = [ 0.08911966  0.01143685  0.03057315  0.0131411 ]
         hidden state #2
         mean = [ 6.59754455e-11
                                    4.32756245e-03 9.77124970e-22
                                                                     2.51896024e-21]
         variance = [ 0.00050009  0.00085585  0.00050009  0.00050009]
         hidden state #3
         mean = [ 0.15715851 -0.00802616 -0.07882145 -0.30428311]
         variance = [ 0.02499005  0.00381481  0.02226397  0.01054853]
         logL = 257.9532970856098
```

```
In [24]: my testword = 'CHOCOLATE'
         model, logL = train_a_word(my_testword, 4, features_norm_polar_coords) # Exper
         iment here with different parameters
         show_model_stats(my_testword, model)
         print("logL = {}".format(logL))
         Number of states trained in model for CHOCOLATE is 4
         hidden state #0
         mean = [ 3.30979923e-01
                                    4.64138086e-01
                                                      3.51761236e-01 -2.08758453e-01
            7.52665677e-03 3.16500921e-04 -1.01021772e-03
                                                               2.40865789e-031
         variance = [ 0.00142054  0.00063018  0.00138223  0.00091643  0.00073207  0.0
         0061309
           0.00103423 0.00096823]
         hidden state #1
         mean = [ 0.45726054  0.47821239  0.49519442  -0.27765755  -0.00885866  0.00393
          -0.01907447 -0.00223042]
         variance = [ 0.00142803  0.00096031  0.00606245  0.0013628  0.00120702  0.0
         0090085
           0.00244372 0.00109839]
         hidden state #2
         mean = [ 0.25693787  0.45443133  0.48646859 -0.2187799  0.00718578  0.00283
         913
          -0.0502764 -0.00990431]
         variance = [ 0.00178148  0.00174985  0.00454189  0.00304516  0.00168599  0.0
         016301
           0.00291674 0.00189159]
         hidden state #3
         mean = [ 0.28427069  0.44999872  0.27170853 -0.26126657  0.01053902 -0.00080
         419
          -0.00609619 -0.00281184]
         variance = [ 0.00216161  0.00081977  0.00180867  0.00091722  0.00112796  0.0
         0081907
           0.0015595
                       0.00083108]
```

logL = 877.5737285688424

```
In [25]: my testword = 'CHOCOLATE'
        model, logL = train_a_word(my_testword, 4, features_custom) # Experiment here
         with different parameters
        show_model_stats(my_testword, model)
        print("logL = {}".format(logL))
        Number of states trained in model for CHOCOLATE is 4
        hidden state #0
        mean = [ 0.68894685 -0.06726488  0.04545047  0.02671352  0.04150469 -0.43023
        168
          -0.07385162 -0.00940697]
        variance = [ 0.06099841  0.14440328  0.01315092  0.00229277  0.04798564  0.0
        0710977
          0.00214024 0.00206358 0.00662637 0.00240703 0.00197695 0.00199185
          0.00206876 0.00243771]
        hidden state #1
        mean = [ 2.70040186e+00
                                 1.36252009e-01
                                                 1.19035544e-01 -2.12498531e-02
          -5.49894403e-03 -7.79920592e-02 4.57260544e-01 4.78212389e-01
           4.95194423e-01 -2.77657546e-01 -8.85866356e-03 3.93144328e-03
          -1.90744719e-02 -2.23041942e-03]
        variance = [ 0.18128913  0.11118816  0.06340054  0.00447343  0.03237197  0.0
        3364657
          0.00142803 0.00096031 0.00606245 0.0013628 0.00120702 0.00090085
          0.00244372 0.00109839]
        hidden state #2
        mean = \begin{bmatrix} 1.66934760e+00 \end{bmatrix}
                                 3.93829880e-02 -5.16630049e-02
                                                                4.85017537e-02
           2.99923837e-02 -1.60076676e-02 2.85946802e-01 4.49787986e-01
           2.66464363e-01 -2.61850817e-01 1.08918419e-02 -1.07368615e-03
          -2.45048058e-03 -4.23092216e-03]
        variance = [ 0.01155148  0.03468306  0.04944696  0.00972004  0.00701598  0.0
        2087937
          0.00223606 0.00086659 0.00141099 0.00096409 0.00119124 0.00086532
          0.00140807 0.00084167]
        hidden state #3
                                 3.88707098e-02 8.72844129e-03
        mean = [ 9.85866138e-01
                                                                4.41029173e-02
          -1.80595855e-02 -2.28400816e-03 3.23267776e-01 4.64368449e-01
           3.69229341e-01 -2.04686504e-01 8.13778195e-03 6.62010383e-04
          -3.48913286e-04 2.29660018e-03]
        1430976
          0.00182059 0.00056857 0.00386049 0.00096373 0.00067952 0.00055369
          0.00088989 0.0008661 ]
```

logL = 1032.0617289350384

```
In [26]:
         my testword = 'CHOCOLATE'
         model, logL = train_a_word(my_testword, 4, features_norm+features_custom) # Ex
         periment here with different parameters
         show model stats(my testword, model)
         print("logL = {}".format(logL))
         Number of states trained in model for CHOCOLATE is 4
        hidden state #0
        mean = [ 3.96427827e-01 -1.89866022e-01 -2.78868852e-01 -1.67283647e+00
           1.66934706e+00 3.93872892e-02 -5.16604607e-02 4.85022802e-02
           2.99920823e-02 -1.60109936e-02 2.85946693e-01
                                                           4.49788134e-01
           2.66464708e-01 -2.61850781e-01 1.08919296e-02 -1.07356630e-03
          -2.45106441e-03 -4.23095236e-03]
         variance = [ 0.07442649  0.02997019  0.01666081  0.01991189  0.01155139  0.0
         3468456
          0.04944711 0.00971997 0.00701592 0.02088026 0.00223604 0.00086659
          0.00141099 0.00096408 0.00119123 0.00086531 0.00140809 0.00084166]
        hidden state #1
        mean = \begin{bmatrix} 5.52775770e-01 & 5.85133921e-02 & 1.12964413e-01 & -7.76093053e-01 \end{bmatrix}
           9.76746406e-01 4.40507571e-02 3.57790738e-03 4.06647112e-02
          -2.01092386e-02 -4.42867042e-03 3.31092050e-01 4.64138718e-01
           3.51638001e-01 -2.08757778e-01
                                            7.52906570e-03 3.38985208e-04
          -6.93103104e-04 2.54923467e-03]
         variance = [ 0.02227333  0.02484758  0.01734906  0.03061802  0.02571509  0.0
         1883522
          0.01340227 0.0048066 0.02116338 0.01655802 0.00141609 0.0006312
          0.00137512 0.0009179 0.00073333 0.00061394 0.00100719 0.00096378]
        hidden state #2
        mean = \begin{bmatrix} 9.89440201e-01 & -1.60060522e-01 & -1.31412901e+00 & -1.55560526e+00 \end{bmatrix}
           2.70040186e+00 1.36252009e-01 1.19035544e-01 -2.12498531e-02
          -5.49894403e-03 -7.79920592e-02 4.57260544e-01 4.78212389e-01
           4.95194423e-01 -2.77657546e-01 -8.85866356e-03 3.93144328e-03
           -1.90744719e-02 -2.23041942e-03]
         variance = [ 0.10711401  0.00555855  0.03518414  0.09325342  0.18128913  0.1
         1118816
          0.06340054 0.00447343 0.03237197 0.03364657 0.00142803 0.00096031
          0.00606245 0.0013628 0.00120702 0.00090085 0.00244372 0.00109839]
        hidden state #3
        mean = \begin{bmatrix} 0.50337677 & -0.3301064 & -0.14973033 & -0.28993689 & 0.7924637 & -0.05067 \end{bmatrix}
        418
          0.04782438 0.03979799 0.0301157 -0.30760774 0.25679133 0.45438067
                                 0.47285298 -0.2222306
         variance = [ 0.02653053  0.00568306  0.02155259  0.22949723  0.07298732  0.1
         0390137
          0.00553362 0.00280777 0.00149858 0.00144919 0.0026252
                                                                   0.00178664]
```

logL = 1104.998275794775

```
In [27]:
        my testword = 'CHOCOLATE'
        model, logL = train_a_word(my_testword, 4, features_norm+features_delta_norm_h
        and pos+features norm polar coords) # Experiment here with different parameter
        show model stats(my testword, model)
        print("logL = {}".format(logL))
        Number of states trained in model for CHOCOLATE is 4
        hidden state #0
        mean = [0.9894402 -0.16006052 -1.31412901 -1.55560526 0.11903554 -0.02124]
        985
         -0.00549894 -0.07799206 0.45726054 0.47821239 0.49519442 -0.27765755
         -0.00885866 0.00393144 -0.01907447 -0.00223042]
        variance = [ 0.10711401  0.00555855  0.03518414  0.09325342  0.06340054  0.0
        0447343
         0.00120702 0.00090085 0.00244372 0.00109839]
        hidden state #1
        mean = \begin{bmatrix} 4.79037344e-01 & 7.91367367e-02 & 9.79743592e-02 & -8.62146688e-01 \end{bmatrix}
         -2.61161494e-02 5.73367891e-02 2.71901101e-03 2.15305168e-02
          3.36697578e-01 4.61142063e-01 3.45034007e-01 -2.17819152e-01
          1.15537939e-02 -3.72086568e-04 3.99250687e-03 6.77476387e-05]
        variance = [ 0.05608837  0.02488282  0.01968713  0.05893709  0.01851001  0.0
        076717
         0.00085338 0.00058095 0.0009923 0.00096877]
        hidden state #2
        mean = [ 4.78777521e-01 -2.54985059e-01 -3.27098990e-01 -1.72163831e+00 ]
         -1.85668704e-02 2.05427458e-02 -3.32030160e-07 -5.01223406e-02
          2.71180329e-01 4.51717217e-01 2.57443253e-01 -2.56525556e-01
          4.54078560e-03 -4.48924444e-04 -8.74369300e-03 -1.13362971e-03
        variance = [ 0.04269708  0.00439304  0.00153578  0.00729357  0.04936689  0.0
        0539733
         0.00111172 0.0010149 0.00139575 0.00092013]
        hidden state #3
        mean = [ 0.52341442 -0.30554653 -0.11814343 -0.30920449  0.05061843  0.04260
        394
         0.02658597 -0.28784369 0.26149914 0.4560152
                                                   0.46494611 -0.22087881
         variance = [ 0.0275096  0.00974941  0.0270948  0.21093919  0.01019394  0.0
        0331733
         0.03125428 0.04450303 0.00157315 0.00140023 0.00548449 0.00250507
         0.00133326  0.00128546  0.00250475  0.00158687]
```

logL = 1111.2326279733452

```
In [28]: my testword = 'FUTURE1'
        model, logL = train_a_word(my_testword, 4, features_ground) # Experiment here
        with different parameters
        show model stats(my testword, model)
        print("logL = {}".format(logL))
        Number of states trained in model for FUTURE1 is 4
        hidden state #0
        mean = [-17.33333333]
                             28.33333333 -18.33333333 124.
                                                                ]
        variance = [ 2.89222222 0.22555556 2.89222222 0.67
                                                            1
        hidden state #1
        variance = [ 0.22555556  0.89222222  0.22555556  0.22555556]
        hidden state #2
        mean = [ -24.66666667 27.33333333 28.3333333 174.666666667]
        variance = [ 1.55888889 0.22555556 0.22555556 0.89222222]
        hidden state #3
        mean = [-20. 34. -22. 125.]
        variance = [ 0.01 0.01 0.01 0.01]
```

logL = -38.19119712135632

```
In [29]:
        my testword = 'FUTURE1'
        model, logL = train_a_word(my_testword, 4, features_norm+features_delta_norm_h
        and pos+features norm polar coords) # Experiment here with different parameter
        show model stats(my testword, model)
        print("logL = {}".format(logL))
        Number of states trained in model for FUTURE1 is 4
        hidden state #0
        mean = \begin{bmatrix} -0.45662122 & -1.06014359 & -0.42330008 & 0.48136381 & -0.00881745 & -0.02732 \end{bmatrix}
        124
         -0.010471 -0.0030763 -0.00169276 -0.00149803]
        variance = [ 0.00858618  0.00447737  0.00662576  0.00227705  0.01231806  0.0
        0285546
                     0.00303476 0.00223105 0.00170947 0.00169562 0.00172922
          0.0114639
          0.00195986 0.00167683 0.00172709 0.00173072]
        hidden state #1
        mean = \begin{bmatrix} -5.28283580e-01 & -7.02051402e-01 & -2.35331659e+00 \end{bmatrix}
                                                                 2.24553767e-01
          -1.34315737e-01 -2.52212462e-02 -1.94948102e-01 3.46920779e-02
           1.96286884e-01 3.88278656e-01 6.02232933e-01 -7.35164870e-02
           4.76159305e-04 -9.44452806e-03 8.95608707e-03 1.54666406e-02]
        1 0.01
          0.01 0.01 0.01 0.01]
        hidden state #2
        mean = [-0.42754626 -0.84076828 -2.09338593 0.17251577 0.03357946 -0.06305
        303
          0.19494724 -0.01734592 0.16697648 0.3809603
                                                      0.58947641 -0.09406567
         -0.01280151 -0.00401991 -0.00575153 -0.01600631]
        variance = [ 0.00612765  0.00515902  0.02189097  0.00530088  0.01514799  0.0
        1279234
          0.00922307 0.00770795 0.00501373 0.00500051 0.00500156 0.0051314
          0.00540868 0.00500663 0.00506819 0.00504789]
        hidden state #3
        mean = \begin{bmatrix} -0.19249424 & -0.85337888 & -2.15836849 & 0.22455377 & 0.26863147 & -0.02522 \end{bmatrix}
        125
         -0.1949481
                     -0.01557265 0.01468697 0.00855339 0.01571052]
        variance = [ 0.01000004 0.01000004 0.01000004 0.01000004 0.01
        1000004
          0.01000004 0.01000004 0.01000004 0.01000004 0.01000004 0.01000004
          0.01000004 0.01000004 0.01000004 0.01000004]
```

logL = 260.6685445714538

```
In [30]:
        my testword = 'FUTURE1'
        model, logL = train_a_word(my_testword, 4, features_norm+features_custom) # Ex
        periment here with different parameters
        show model stats(my testword, model)
        print("logL = {}".format(logL))
        Number of states trained in model for FUTURE1 is 4
        hidden state #0
        mean = [ -4.56621224e-01 -1.06014359e+00 -4.23300079e-01
                                                                4.81363812e-01
           1.54200037e+00 2.95729979e-02 -8.81744771e-03 -2.73212398e-02
          -3.29936642e-02 4.58776819e-03 2.05661200e-01 3.59827620e-01
           9.09549414e-01 -2.99611432e-01 -1.04710035e-02 -3.07629647e-03
          -1.69275994e-03 -1.49803443e-03]
        variance = [ 0.00858618  0.00447737  0.00662576  0.00227705  0.00647859  0.0
        0399676
          0.01231806 0.00285546 0.0114639 0.00303476 0.00223105 0.00170947
          0.00169562 0.00172922 0.00195986 0.00167683 0.00172709 0.00173072
        hidden state #1
        mean = \begin{bmatrix} -0.19249424 & -0.85337888 & -2.15836849 & 0.22455377 & 2.24200811 & 0.42727 \end{bmatrix}
          0.5992832 -0.08981874 -0.01557265 0.01468697 0.00855339 0.01571052]
        1 0.01
          0.01 0.01 0.01 0.01 0.01 0.01]
        hidden state #2
        mean = \begin{bmatrix} -4.61125711e-01 & -7.77715140e-01 & -2.28833389e+00 \end{bmatrix}
                                                                1.89861689e-01
           2.06788132e+00 6.16005180e-02 2.62818242e-20 -8.82743615e-02
          -3.24913503e-02 -1.73460390e-02 1.79778010e-01 3.84980224e-01
           5.95227949e-01 -7.80592955e-02 -1.62707951e-02 -8.02069591e-03
                          3.19051175e-03]
          -2.52694032e-03
        variance = [ 0.00951018  0.010725  0.00922275  0.00620354  0.00544491  0.0
        0537693
          0.02304072 0.0089757 0.0313922 0.00770797 0.00527254 0.00501088
          0.00504907 0.00502064 0.00528046 0.00500203 0.00513186 0.0051507 ]
        hidden state #3
        mean = \begin{bmatrix} -4.61125711e-01 & -8.28157633e-01 & -1.96342039e+00 \end{bmatrix}
                                                                1.89861689e-01
           1.81473211e+00 -2.74242156e-01 -6.71578683e-02 2.52212462e-02
                                         1.70683886e-01 3.80238751e-01
           2.59930803e-01 3.46920779e-02
           5.90729810e-01 -1.05529256e-01 7.41475106e-03 -1.44304070e-03
           2.50684527e-03 -2.29271518e-02]
        1 0.01
          0.01 0.01 0.01 0.01 0.01 0.01]
```

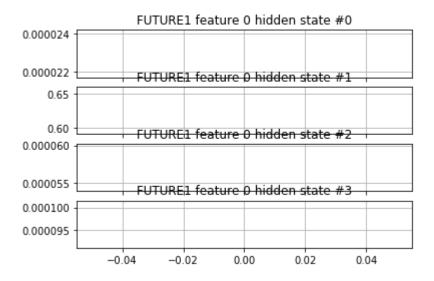
logL = 286.6984478044842

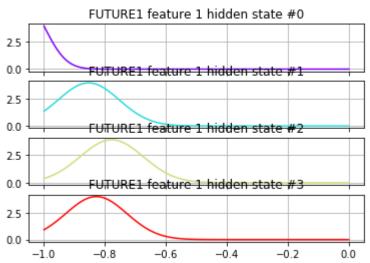
## Visualize the hidden states

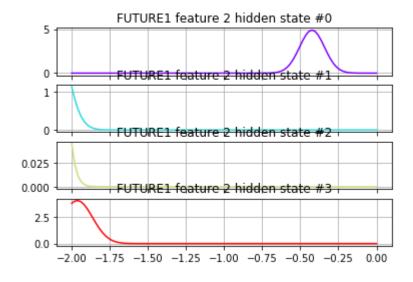
We can plot the means and variances for each state and feature. Try varying the number of states trained for the HMM model and examine the variances. Are there some models that are "better" than others? How can you tell? We would like to hear what you think in the classroom online.

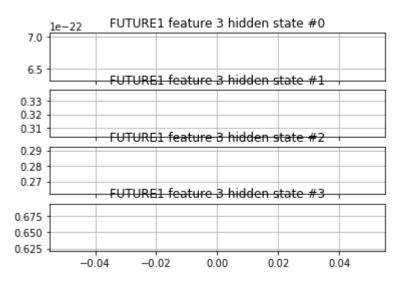
In [31]: %matplotlib inline

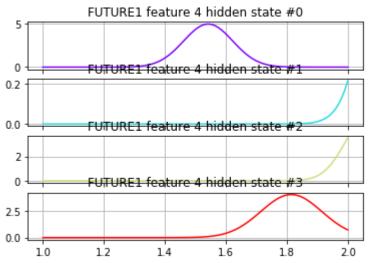
```
In [32]:
         import math
         from matplotlib import (cm, pyplot as plt, mlab)
         def visualize(word, model):
              """ visualize the input model for a particular word """
             variance=np.array([np.diag(model.covars_[i]) for i in range(model.n_compon
         ents)])
             figures = []
             for parm_idx in range(len(model.means_[0])):
                 xmin = int(min(model.means_[:,parm_idx]) - max(variance[:,parm_idx]))
                 xmax = int(max(model.means_[:,parm_idx]) + max(variance[:,parm_idx]))
                 fig, axs = plt.subplots(model.n_components, sharex=True, sharey=False)
                 colours = cm.rainbow(np.linspace(0, 1, model.n_components))
                 for i, (ax, colour) in enumerate(zip(axs, colours)):
                     x = np.linspace(xmin, xmax, 100)
                     mu = model.means_[i,parm_idx]
                     sigma = math.sqrt(np.diag(model.covars_[i])[parm_idx])
                     ax.plot(x, mlab.normpdf(x, mu, sigma), c=colour)
                     ax.set_title("{} feature {} hidden state #{}".format(word, parm_id
         x, i))
                     ax.grid(True)
                 figures.append(plt)
             for p in figures:
                 p.show()
         visualize(my testword, model)
```



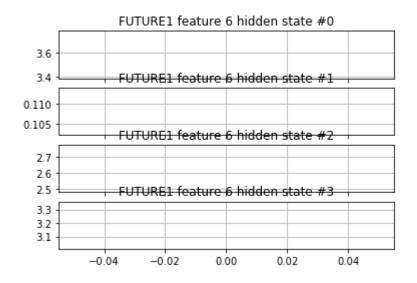


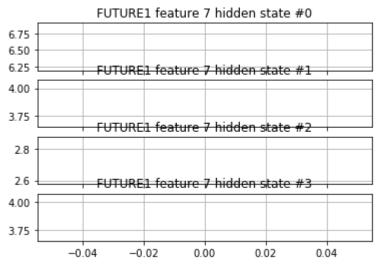


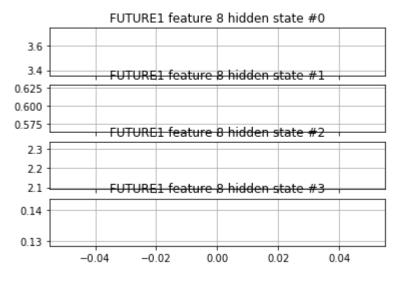


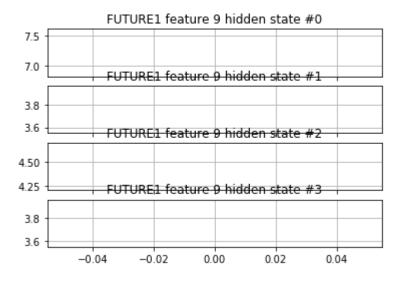


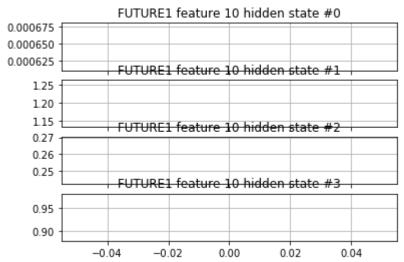


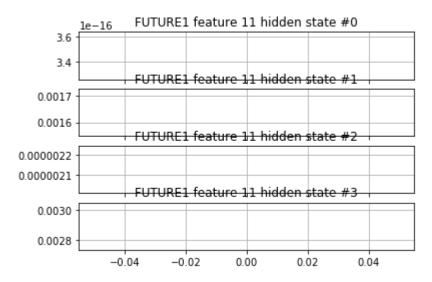


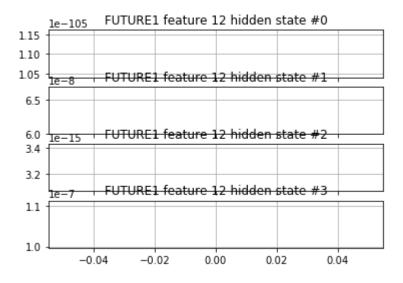


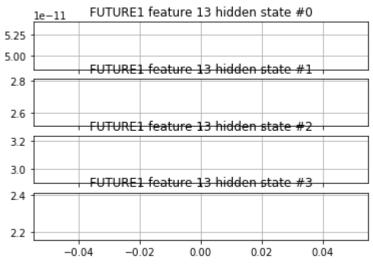


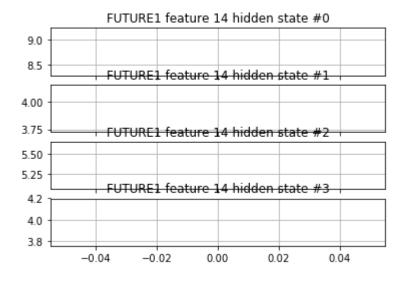


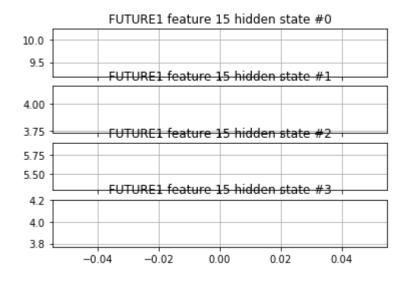


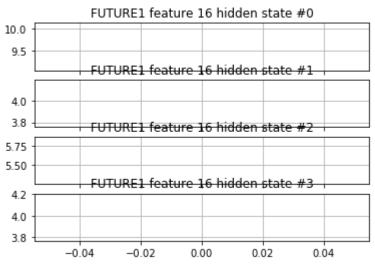


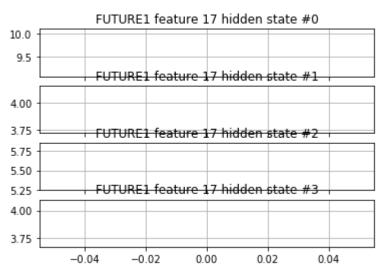












#### ModelSelector class

Review the ModelSelector class from the codebase found in the my\_model\_selectors.py module. It is designed to be a strategy pattern for choosing different model selectors. For the project submission in this section, subclass SelectorModel to implement the following model selectors. In other words, you will write your own classes/functions in the my\_model\_selectors.py module and run them from this notebook:

SelectorCV: Log likelihood with CV

SelectorBIC: BICSelectorDIC: DIC

You will train each word in the training set with a range of values for the number of hidden states, and then score these alternatives with the model selector, choosing the "best" according to each strategy. The simple case of training with a constant value for n\_components can be called using the provided SelectorConstant subclass as follow:

```
In [33]: from my_model_selectors import SelectorConstant

    training = asl.build_training(features_ground) # Experiment here with differe
    nt feature sets defined in part 1
    word = 'VEGETABLE' # Experiment here with different words
    model = SelectorConstant(training.get_all_sequences(), training.get_all_Xlengt
    hs(), word, n_constant=3).select()
    print("Number of states trained in model for {} is {}".format(word, model.n_co
    mponents))
```

Number of states trained in model for VEGETABLE is 3

#### Cross-validation folds

If we simply score the model with the Log Likelihood calculated from the feature sequences it has been trained on, we should expect that more complex models will have higher likelihoods. However, that doesn't tell us which would have a better likelihood score on unseen data. The model will likely be overfit as complexity is added. To estimate which topology model is better using only the training data, we can compare scores using cross-validation. One technique for cross-validation is to break the training set into "folds" and rotate which fold is left out of training. The "left out" fold scored. This gives us a proxy method of finding the best model to use on "unseen data". In the following example, a set of word sequences is broken into three folds using the <a href="scikit-learn-kfold">scikit-learn.org/stable/modules/generated/sklearn.model\_selection.KFold.html</a>) class object. When you implement SelectorCV, you will use this technique.

In [ ]:	
---------	--

```
In [34]: from sklearn.model_selection import KFold

training = asl.build_training(features_ground) # Experiment here with differen
    t feature sets
word = 'VEGETABLE' # Experiment here with different words
word_sequences = training.get_word_sequences(word)
split_method = KFold()
for cv_train_idx, cv_test_idx in split_method.split(word_sequences):
    print("Train fold indices:{} Test fold indices:{}".format(cv_train_idx, cv_test_idx)) # view indices of the folds

Train fold indices:[2 3 4 5] Test fold indices:[0 1]
Train fold indices:[0 1 4 5] Test fold indices:[2 3]
Train fold indices:[0 1 2 3] Test fold indices:[4 5]
```

**Tip:** In order to run hmmlearn training using the X,lengths tuples on the new folds, subsets must be combined based on the indices given for the folds. A helper utility has been provided in the asl\_utils module named combine sequences for this purpose.

## Scoring models with other criterion

Scoring model topologies with **BIC** balances fit and complexity within the training set for each word. In the BIC equation, a penalty term penalizes complexity to avoid overfitting, so that it is not necessary to also use cross-validation in the selection process. There are a number of references on the internet for this criterion. These <u>slides (http://www2.imm.dtu.dk/courses/02433/doc/ch6\_slides.pdf)</u> include a formula you may find helpful for your implementation.

The advantages of scoring model topologies with **DIC** over BIC are presented by Alain Biem in this <u>reference</u> (<a href="http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.58.6208&rep=rep1&type=pdf">https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.58.6208&rep=rep1&type=pdf</a>) (also found <a href="https://pdfs.semanticscholar.org/ed3d/7c4a5f607201f3848d4c02dd9ba17c791fc2.pdf">https://pdfs.semanticscholar.org/ed3d/7c4a5f607201f3848d4c02dd9ba17c791fc2.pdf</a>)). DIC scores the discriminant ability of a training set for one word against competing words. Instead of a penalty term for complexity, it provides a penalty if model liklihoods for non-matching words are too similar to model likelihoods for the correct word in the word set.

## **Model Selection Implementation Submission**

Implement SelectorCV, SelectorBIC, and SelectorDIC classes in the my\_model\_selectors.py module. Run the selectors on the following five words. Then answer the questions about your results.

**Tip:** The hmmlearn library may not be able to train or score all models. Implement try/except contructs as necessary to eliminate non-viable models from consideration.

```
In [35]: words_to_train = ['FISH', 'BOOK', 'VEGETABLE', 'FUTURE', 'JOHN']
import timeit
```

```
In [36]: # TODO: Implement SelectorCV in my model selector.py
         from importlib import reload
         import my model selectors
         reload(my model selectors)
         from my model selectors import SelectorCV
         training = asl.build_training(features_ground) # Experiment here with differe
         nt feature sets defined in part 1
         sequences = training.get_all_sequences()
         Xlengths = training.get_all_Xlengths()
         for word in words_to_train:
             start = timeit.default_timer()
             model = SelectorCV(sequences, Xlengths, word,
                             min n components=2, max n components=15, random state =
         14).select()
             end = timeit.default_timer()-start
             if model is not None:
                 print("Training complete for {} with {} states with time {} seconds".f
         ormat(word, model.n_components, end))
             else:
                 print("Training failed for {}".format(word))
```

Training complete for FISH with 7 states with time 0.3083498827903513 seconds Training complete for BOOK with 15 states with time 2.910612832975545 seconds Training complete for VEGETABLE with 15 states with time 1.326159472824569 se conds

Training complete for FUTURE with 15 states with time 2.8371819048613087 seconds

Training complete for JOHN with 15 states with time 27.876576547350723 second s

```
In [37]: # TODO: Implement SelectorCV in my model selector.py
         from importlib import reload
         import my model selectors
         reload(my model selectors)
         from my model selectors import SelectorCV
         training = asl.build training(features norm+features custom) # Experiment her
         e with different feature sets defined in part 1
         sequences = training.get_all_sequences()
         Xlengths = training.get_all_Xlengths()
         for word in words to train:
             start = timeit.default_timer()
             model = SelectorCV(sequences, Xlengths, word,
                             min n components=2, max n components=15, random state =
         14).select()
             end = timeit.default_timer()-start
             if model is not None:
                 print("Training complete for {} with {} states with time {} seconds".f
         ormat(word, model.n_components, end))
             else:
                 print("Training failed for {}".format(word))
```

Training complete for FISH with 4 states with time 0.3036981689342255 seconds Training complete for BOOK with 15 states with time 2.8749735537796255 second s

Training complete for VEGETABLE with 5 states with time 1.235572352627564 sec onds

Training complete for FUTURE with 15 states with time 2.2185272346703613 seconds

Training complete for JOHN with 15 states with time 39.56817800351487 seconds

```
In [38]: # TODO: Implement SelectorBIC in module my model selectors.py
         from my model selectors import SelectorBIC
         training = asl.build training(features ground) # Experiment here with differe
         nt feature sets defined in part 1
         sequences = training.get_all_sequences()
         Xlengths = training.get all Xlengths()
         for word in words to train:
             start = timeit.default timer()
             model = SelectorBIC(sequences, Xlengths, word,
                             min n components=2, max n components=15, random state =
         14).select()
             end = timeit.default_timer()-start
             if model is not None:
                 print("Training complete for {} with {} states with time {} seconds".f
         ormat(word, model.n_components, end))
             else:
                 print("Training failed for {}".format(word))
         Training complete for FISH with 2 states with time 0.2658166028666358 seconds
         Training complete for BOOK with 15 states with time 1.5043163757817553 second
         Training complete for VEGETABLE with 2 states with time 0.5257420456821364 se
         Training complete for FUTURE with 15 states with time 1.6543623569435795 seco
         Training complete for JOHN with 2 states with time 14.844436632035055 seconds
```

In [39]: # TODO: Implement SelectorBIC in module my model selectors.py from my model selectors import SelectorBIC training = asl.build training(features norm+features custom) # Experiment her e with different feature sets defined in part 1 sequences = training.get\_all\_sequences() Xlengths = training.get\_all\_Xlengths() for word in words to train: start = timeit.default\_timer() model = SelectorBIC(sequences, Xlengths, word, min\_n\_components=2, max\_n\_components=15, random\_state = 14).select() end = timeit.default timer()-start if model is not None: print("Training complete for {} with {} states with time {} seconds".f ormat(word, model.n components, end)) else: print("Training failed for {}".format(word))

Training complete for FISH with 15 states with time 0.3023695108225013 second s

Training complete for BOOK with 15 states with time 1.4444029924427184 second s

Training complete for VEGETABLE with 15 states with time 0.5401696930545938 s econds

Training complete for FUTURE with 15 states with time 1.3152012169492764 seconds

Training complete for JOHN with 2 states with time 25.74557396055775 seconds

```
In [40]: # TODO: Implement SelectorDIC in module my model selectors.py
         from my model selectors import SelectorDIC
         training = asl.build training(features ground) # Experiment here with differe
         nt feature sets defined in part 1
         sequences = training.get_all_sequences()
         Xlengths = training.get all Xlengths()
         for word in words to train:
             start = timeit.default timer()
             model = SelectorDIC(sequences, Xlengths, word,
                             min n components=2, max n components=15, random state =
         14).select()
             end = timeit.default_timer()-start
             if model is not None:
                 print("Training complete for {} with {} states with time {} seconds".f
         ormat(word, model.n_components, end))
             else:
                 print("Training failed for {}".format(word))
```

Training complete for FISH with 3 states with time 0.6576117158871853 seconds Training complete for BOOK with 15 states with time 3.456917343924971 seconds Training complete for VEGETABLE with 15 states with time 2.3486324130518597 s econds Training complete for FUTURE with 15 states with time 3.3170492788292165 seconds Training complete for JOHN with 15 states with time 17.014176937203274 second s

```
In [41]: # TODO: Implement SelectorDIC in module my model selectors.py
         from my model selectors import SelectorDIC
         training = asl.build training(features norm+features custom) # Experiment her
         e with different feature sets defined in part 1
         sequences = training.get_all_sequences()
         Xlengths = training.get_all_Xlengths()
         for word in words to train:
             start = timeit.default_timer()
             model = SelectorDIC(sequences, Xlengths, word,
                             min_n_components=2, max_n_components=15, random_state =
         14).select()
             end = timeit.default timer()-start
             if model is not None:
                 print("Training complete for {} with {} states with time {} seconds".f
         ormat(word, model.n components, end))
             else:
                 print("Training failed for {}".format(word))
```

Training complete for FISH with 2 states with time 1.919399677849782 seconds Training complete for BOOK with 15 states with time 2.898894689034762 seconds Training complete for VEGETABLE with 7 states with time 2.3590116730090642 seconds

Training complete for FUTURE with 15 states with time 2.977831014998884 seconds

Training complete for JOHN with 15 states with time 24.78913723261107 seconds

**Question 2:** Compare and contrast the possible advantages and disadvantages of the various model selectors implemented.

#### Answer 2:

Selector CV shows itself to us as the slowest algorithym, in contrast with with the SelectorDIC and SelectorBIC nearly matched runtimes.BIC does come out slightly faster on our test words, even when the tested with different feature sets, but this is expected as it is slightly less complex. Our DIC selector could be further opimized by using a cache to prevent re-scoring words we have already seen, but it is unlikely this would speed it enough to beat the BIC selector. We can see the some signs that the BIC and DIC selectors are overfitting, as they have tended to select models with more states, but we also saw this with CV which is designed to prevent overfitting.

## **Model Selector Unit Testing**

Run the following unit tests as a sanity check on the implemented model selectors. The test simply looks for valid interfaces but is not exhaustive. However, the project should not be submitted if these tests don't pass.

# PART 3: Recognizer

The objective of this section is to "put it all together". Using the four feature sets created and the three model selectors, you will experiment with the models and present your results. Instead of training only five specific words as in the previous section, train the entire set with a feature set and model selector strategy.

## **Recognizer Tutorial**

### Train the full training set

The following example trains the entire set with the example features\_ground and SelectorConstant features and model selector. Use this pattern for you experimentation and final submission cells.

```
In [81]: # autoreload for automatically reloading changes made in my model selectors an
         d my recognizer
         %load ext autoreload
         %autoreload 2
         from my model selectors import SelectorConstant
         def train_all_words(features, model_selector):
             training = asl.build training(features) # Experiment here with different
          feature sets defined in part 1
             sequences = training.get_all_sequences()
             Xlengths = training.get_all_Xlengths()
             model_dict = {}
             for word in training.words:
                 model = model selector(sequences, Xlengths, word,
                                  n_constant=3).select()
                 model dict[word]=model
             return model dict
         models = train all words(features norm+features custom, SelectorConstant)
         print("Number of word models returned = {}".format(len(models)))
         The autoreload extension is already loaded. To reload it, use:
```

### Load the test set

The build\_test method in ASLdb is similar to the build\_training method already presented, but there are a few differences:

· the object is type SinglesData

%reload ext autoreload

Number of word models returned = 112

- the internal dictionary keys are the index of the test word rather than the word itself
- the getter methods are get\_all\_sequences, get\_all\_Xlengths, get\_item\_sequences and get item Xlengths

### **Recognizer Implementation Submission**

For the final project submission, students must implement a recognizer following guidance in the my\_recognizer.py module. Experiment with the four feature sets and the three model selection methods (that's 12 possible combinations). You can add and remove cells for experimentation or run the recognizers locally in some other way during your experiments, but retain the results for your discussion. For submission, you will provide code cells of **only three** interesting combinations for your discussion (see questions below). At least one of these should produce a word error rate of less than 60%, i.e. WER < 0.60.

**Tip:** The hmmlearn library may not be able to train or score all models. Implement try/except contructs as necessary to eliminate non-viable models from consideration.

In [79]: # TODO implement the recognize method in my\_recognizer
from my\_recognizer import recognize
from asl\_utils import show\_errors

```
In [73]: # TODO Choose a feature set and model selector
    features = features_norm+features_custom # change as needed
    model_selector = SelectorBIC # change as needed

# TODO Recognize the test set and display the result with the show_errors meth
    od
    models = train_all_words(features, model_selector)
    test_set = asl.build_test(features)
    probabilities, guesses = recognize(models, test_set)
    show_errors(guesses, test_set)
```

\*\*\*\* WER = 0.5168539325842697 Total correct: 86 out of 178

Total correct: 86 out of 178	
Video Recognized	Correct
	=======
2: *MARY WRITE *ARRIVE	JOHN WRI
TE HOMEWORK	
7: JOHN *CAR GO CAN	JOHN CAN
GO CAN	JOHN CAN
12: JOHN CAN *GO1 CAN GO CAN	JOHN CAN
21: JOHN *JOHN *VISIT *JOHN *CAR *CAR *FUTURE *FUTURE	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	
25: JOHN *MARY *MARY *LIKE *LOVE	JOHN LIK
E IX IX IX	
28: JOHN LIKE *MARY *MARY *LOVE	JOHN LIK
E IX IX IX	JOHN LTV
30: JOHN LIKE *MARY *MARY IX E IX IX IX	JOHN LIK
36: MARY *WHO *GIVE3 *WOMAN LIKE *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1	120
40: *MARY *MARY *CORN *VEGETABLE *MARY	JOHN IX
THINK MARY LOVE	
43: JOHN *SHOULD BUY HOUSE	JOHN MUS
T BUY HOUSE	EUTURE 3
50: FUTURE *SEE BUY CAR *MARY OHN BUY CAR SHOULD	FUTURE J
54: JOHN *FUTURE *FUTURE BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	301114 3110
57: JOHN *MARY *GO MARY	JOHN DEC
IDE VISIT MARY	
67: JOHN FUTURE NOT BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	701111
71: JOHN *FUTURE VISIT MARY L VISIT MARY	JOHN WIL
74: JOHN *MARY *MARY MARY	JOHN NOT
VISIT MARY	301114 1401
77: *JOHN BLAME MARY	ANN BLAM
E MARY	
84: *IX *ARRIVE *VISIT BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	
89: *SOMETHING-ONE IX *SOMETHING-ONE *CANDY IX *BOOK COAT	JOHN IX
GIVE MAN IX NEW COAT 90: *PREFER *GIVE1 IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
92: JOHN *GIVE1 IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
100: POSS NEW CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	
105: JOHN *WHO	JOHN LEG
107: *SHOULD POSS *CAR *MARY *MARY S FRIEND HAVE CANDY	JOHN POS
108: *SOMETHING-ONE ARRIVE	WOMAN AR
RIVE	AU FIN AN
113: *JOHN CAR *CAR *MARY *ARRIVE	IX CAR B
LUE SUE BUY	
119: *PREFER *BUY1 *GO CAR *VISIT	SUE BUY

```
IX CAR BLUE
           122: JOHN *GIVE1 BOOK
                                                                                JOHN REA
         D BOOK
           139: JOHN *BUY1 WHAT YESTERDAY BOOK
                                                                                JOHN BUY
         WHAT YESTERDAY BOOK
           142: JOHN BUY YESTERDAY WHAT BOOK
                                                                                JOHN BUY
         YESTERDAY WHAT BOOK
           158: LOVE *MARY *MARY
                                                                                LOVE JOH
         N WHO
           167: *MARY IX *MARY LOVE MARY
                                                                                JOHN IX
          SAY LOVE MARY
           171: *MARY *JOHN BLAME
                                                                                JOHN MAR
         Y BLAME
           174: *GIVE1 *GIVE1 GIVE1 *MARY *VISIT
                                                                                PEOPLE G
         ROUP GIVE1 JANA TOY
           181: JOHN *GIVE1
                                                                                JOHN ARR
         IVE
           184: *IX *YESTERDAY *GIVE1 TEACHER APPLE
                                                                                ALL BOY
          GIVE TEACHER APPLE
           189: *JANA *GIVE3 *CORN *ARRIVE
                                                                                JOHN GIV
         E GIRL BOX
           193: JOHN *POSS *NOT BOX
                                                                                JOHN GIV
         E GIRL BOX
           199: *JOHN *ARRIVE WHO
                                                                                LIKE CHO
         COLATE WHO
           201: JOHN *FUTURE MARY *LIKE BUY HOUSE
                                                                                JOHN TEL
         L MARY IX-1P BUY HOUSE
Out[73]: 0.5168539325842697
         #set up a function of the above for the above, for better re-use!
In [74]:
         def recognize and display result(features = features norm+features custom, mod
         el selector = SelectorCV):
             models = train all words(features, model selector)
             test set = asl.build test(features)
             probabilities, guesses = recognize(models, test set)
             show_errors(guesses, test_set)
In [91]:
         # feature sets I may use
         features ground
         features norm
         features_polar
         features delta
         features custom=features hand dist+features delta norm hand pos+features norm
         polar coords
         features best=features norm+features custom
         feature_sets=[features_ground, features_norm,features_polar,features_delta,fea
         tures_hand_dist,features_delta_norm_hand_pos,features_norm_polar_coords,featur
         es custom, features best]
         # selectors I may use
          selector sets=[SelectorConstant,SelectorBIC,SelectorDIC,SelectorCV]
```

```
In [76]: feature_model_scores=[]
    for chosen_feature in feature_sets:
        for model_selector in selector_sets:
            print("----running:", chosen_feature, model_selector)
            recognize_and_display_result(chosen_feature, model_selector)
```

----running: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my\_model\_se lectors.SelectorConstant'>

\*\*\*\* WER = 0.6685393258426966 Total correct: 59 out of 178 Video Recognized Correct \_\_\_\_\_\_ 2: \*GO WRITE \*ARRIVE JOHN WRI TE HOMEWORK 7: \*SOMETHING-ONE \*GO1 \*IX CAN JOHN CAN GO CAN 12: JOHN \*HAVE \*WHAT CAN JOHN CAN GO CAN 21: JOHN \*HOMEWORK \*NEW \*PREFER \*CAR \*CAR \*FUTURE \*EAT JOHN FIS H WONT EAT BUT CAN EAT CHICKEN 25: \*FRANK \*TELL \*LOVE \*TELL \*LOVE JOHN LIK E IX IX IX 28: \*FRANK \*TELL \*LOVE \*TELL \*LOVE JOHN LIK E IX IX IX 30: \*SHOULD LIKE \*GO \*GO \*GO JOHN LIK E IX IX IX 36: \*VISIT VEGETABLE \*YESTERDAY \*GIVE \*MARY \*MARY MARY VEG ETABLE KNOW IX LIKE CORN1 40: \*SUE \*GIVE \*CORN \*VEGETABLE \*GO JOHN IX THINK MARY LOVE 43: \*FRANK \*GO BUY HOUSE JOHN MUS T BUY HOUSE 50: \*FRANK \*SEE BUY CAR \*SOMETHING-ONE FUTURE J OHN BUY CAR SHOULD 54: JOHN SHOULD \*WHO BUY HOUSE JOHN SHO ULD NOT BUY HOUSE 57: \*MARY \*VISIT VISIT \*VISIT JOHN DEC IDE VISIT MARY 67: \*LIKE FUTURE NOT BUY HOUSE JOHN FUT URE NOT BUY HOUSE 71: JOHN \*FINISH VISIT MARY JOHN WIL L VISIT MARY 74: \*IX \*VISIT \*GO \*GO JOHN NOT VISIT MARY 77: \*JOHN BLAME \*LOVE ANN BLAM E MARY 84: \*LOVE \*ARRIVE \*HOMEWORK BOOK IX-1P FI ND SOMETHING-ONE BOOK 89: \*GIVE \*GIVE GIVE \*IX IX \*ARRIVE \*BOOK JOHN IX GIVE MAN IX NEW COAT 90: \*SOMETHING-ONE \*SOMETHING-ONE IX \*IX WOMAN \*COAT JOHN GIV E IX SOMETHING-ONE WOMAN BOOK 92: \*FRANK GIVE \*WOMAN \*WOMAN WOMAN BOOK JOHN GIV E IX SOMETHING-ONE WOMAN BOOK 100: POSS NEW CAR BREAK-DOWN POSS NEW CAR BREAK-DOWN 105: \*FRANK \*VEGETABLE JOHN LEG 107: \*SHOULD \*IX FRIEND \*GO \*JANA JOHN POS S FRIEND HAVE CANDY 108: \*GIVE \*LOVE WOMAN AR

RIVE

113: IX CAR *CAR *IX *IX	IX CAR B
LUE SUE BUY 119: *PREFER *BUY1 IX *BLAME *IX IX CAR BLUE	SUE BUY
122: JOHN *GIVE1 *COAT	JOHN REA
D BOOK  139: *SHOULD *BUY1 *CAR *BLAME BOOK	JOHN BUY
WHAT YESTERDAY BOOK  142: *FRANK *STUDENT YESTERDAY *TEACHER BOOK	JOHN BUY
YESTERDAY WHAT BOOK 158: LOVE *MARY WHO	LOVE JOH
N WHO 167: *MARY IX *VISIT *WOMAN *LOVE	JOHN IX
SAY LOVE MARY 171: *VISIT *VISIT BLAME	JOHN MAR
Y BLAME 174: *CAN *GIVE3 GIVE1 *APPLE *WHAT	PEOPLE G
ROUP GIVE1 JANA TOY 181: *BLAME ARRIVE	JOHN ARR
IVE 184: *GIVE1 BOY *GIVE1 TEACHER APPLE	ALL BOY
GIVE TEACHER APPLE  189: *JANA *SOMETHING-ONE *YESTERDAY *WHAT	JOHN GIV
E GIRL BOX	
193: JOHN *SOMETHING-ONE *YESTERDAY BOX E GIRL BOX	JOHN GIV
199: *LOVE CHOCOLATE WHO COLATE WHO	LIKE CHO
201: JOHN *GIVE *GIVE *LOVE *ARRIVE HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	301 122
<pre>L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'=""> **** WER = 0.6685393258426966</class></pre>	
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'="">  **** WER = 0.6685393258426966 Total correct: 59 out of 178 Video Recognized</class>	_model_se Correct
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'="">  **** WER = 0.6685393258426966 Total correct: 59 out of 178</class>	_model_se Correct
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'="">  **** WER = 0.6685393258426966 Total correct: 59 out of 178 Video Recognized ====================================</class>	_model_se Correct
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'="">  **** WER = 0.6685393258426966  Total correct: 59 out of 178  Video Recognized</class>	_model_se Correct
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'="">  **** WER = 0.6685393258426966 Total correct: 59 out of 178 Video Recognized ====================================</class>	_model_se Correct ======
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'="">  **** WER = 0.6685393258426966 Total correct: 59 out of 178 Video Recognized</class>	Correct JOHN WRI JOHN CAN
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'="">  **** WER = 0.6685393258426966  Total correct: 59 out of 178  Video Recognized</class>	Correct JOHN WRI JOHN CAN
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'="">  **** WER = 0.6685393258426966  Total correct: 59 out of 178  Video Recognized</class>	Correct JOHN WRI JOHN CAN JOHN CAN JOHN FIS
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'="">  **** WER = 0.6685393258426966 Total correct: 59 out of 178 Video Recognized</class>	Correct JOHN WRI JOHN CAN JOHN CAN JOHN FIS JOHN LIK
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'="">  **** WER = 0.6685393258426966 Total correct: 59 out of 178 Video Recognized </class>	Correct JOHN WRI JOHN CAN JOHN FIS JOHN LIK JOHN LIK
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'="">  **** WER = 0.6685393258426966 Total correct: 59 out of 178 Video Recognized</class>	Correct JOHN WRI JOHN CAN JOHN FIS JOHN LIK JOHN LIK JOHN LIK MARY VEG
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'="">  **** WER = 0.6685393258426966 Total correct: 59 out of 178 Video Recognized</class>	Correct JOHN WRI JOHN CAN JOHN FIS JOHN LIK JOHN LIK

T BUY HOUSE	FUTURE 3
50: *FRANK *SEE *ARRIVE CAR *ARRIVE OHN BUY CAR SHOULD	FUTURE J
54: JOHN *GIVE NOT BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	301114 3110
57: *MARY *MARY MARY	JOHN DEC
IDE VISIT MARY	
67: *LIKE *MOTHER *MARY BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN *FUTURE *GIVE1 *GIVE1	JOHN WIL
L VISIT MARY	TOUR NOT
74: *MARY *BILL *MARY MARY VISIT MARY	JOHN NOT
77: *LOVE BLAME *LOVE	ANN BLAM
E MARY	ANN DEAM
84: *LOVE *ARRIVE *GO BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	
89: *GIVE *GIVE GIVE *GIVE IX *ARRIVE *BOOK	JOHN IX
GIVE MAN IX NEW COAT	
90: *POSS *IX IX *IX WOMAN *HERE	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	70.00
92: *IX-1P GIVE *GIVE *GIVE WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK 100: POSS NEW CAR *BOOK	POSS NEW
CAR BREAK-DOWN	POSS NEW
105: JOHN *SEE	JOHN LEG
107: *LIKE *IX *ARRIVE *VISIT *WHO	JOHN POS
S FRIEND HAVE CANDY	
108: *GIVE *LOVE	WOMAN AR
RIVE	
113: IX CAR BLUE SUE *ARRIVE	IX CAR B
LUE SUE BUY	CHE DIN
119: *PREFER *BUY1 IX *WHAT *SUE IX CAR BLUE	SUE BUY
122: JOHN *CHICAGO BOOK	JOHN REA
D BOOK	301111 11271
139: *SHOULD *BUY1 *CAR *VISIT BOOK	JOHN BUY
WHAT YESTERDAY BOOK	
142: JOHN BUY YESTERDAY *CAN BOOK	JOHN BUY
YESTERDAY WHAT BOOK	
158: LOVE *MARY *VEGETABLE	LOVE JOH
N WHO	JOHN TV
167: *MARY *SUE *BILL LOVE *LOVE SAY LOVE MARY	JOHN IX
171: *SUE *SUE BLAME	JOHN MAR
Y BLAME	Some riskit
174: *WHAT *SOMETHING-ONE GIVE1 *WHO *WHAT	PEOPLE G
ROUP GIVE1 JANA TOY	
101. *CO ADDIVE	
181: *GO ARRIVE	JOHN ARR
IVE	
IVE 184: *IX *GIVE1 TEACHER *MARY	JOHN ARR
IVE 184: *IX *IX *GIVE1 TEACHER *MARY GIVE TEACHER APPLE	ALL BOY
IVE 184: *IX *IX *GIVE1 TEACHER *MARY GIVE TEACHER APPLE 189: *JANA GIVE *IX *CAN	
IVE 184: *IX *IX *GIVE1 TEACHER *MARY GIVE TEACHER APPLE 189: *JANA GIVE *IX *CAN E GIRL BOX	ALL BOY
IVE 184: *IX *IX *GIVE1 TEACHER *MARY GIVE TEACHER APPLE 189: *JANA GIVE *IX *CAN	ALL BOY
IVE  184: *IX *IX *GIVE1 TEACHER *MARY  GIVE TEACHER APPLE  189: *JANA GIVE *IX *CAN  E GIRL BOX  193: JOHN *IX *YESTERDAY BOX	ALL BOY

COLATE WHO 201: JOHN \*GIVE \*GIVE \*JOHN \*BOOK HOUSE JOHN TEL L MARY IX-1P BUY HOUSE ----running: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my\_model\_se lectors.SelectorDIC'> \*\*\*\* WER = 0.5730337078651685 Total correct: 76 out of 178 Video Recognized Correct \_\_\_\_\_\_ 2: JOHN \*NEW \*GIVE1 JOHN WRI TE HOMEWORK 7: \*SOMETHING-ONE \*CAR \*ARRIVE \*ARRIVE JOHN CAN GO CAN 12: \*IX \*WHAT \*WHAT \*CAR JOHN CAN GO CAN 21: JOHN \*GIVE1 \*JOHN \*FUTURE \*CAR \*CAR \*FUTURE \*MARY JOHN FIS H WONT EAT BUT CAN EAT CHICKEN 25: JOHN \*IX IX \*WHO IX JOHN LIK E IX IX IX 28: JOHN \*WHO IX IX \*LOVE JOHN LIK E IX IX IX JOHN LIK 30: JOHN \*MARY \*MARY \*MARY \*MARY E IX IX IX 36: \*VISIT \*VISIT \*GIVE \*GO \*MARY \*IX MARY VEG ETABLE KNOW IX LIKE CORN1 40: \*MARY \*GO \*GIVE MARY \*MARY JOHN IX THINK MARY LOVE 43: JOHN \*IX BUY HOUSE JOHN MUS T BUY HOUSE 50: \*JOHN \*FUTURE \*GIVE1 CAR \*JOHN FUTURE J OHN BUY CAR SHOULD 54: JOHN SHOULD NOT BUY HOUSE JOHN SHO ULD NOT BUY HOUSE 57: \*MARY \*VISIT VISIT MARY JOHN DEC IDE VISIT MARY 67: JOHN FUTURE \*MARY BUY HOUSE JOHN FUT URE NOT BUY HOUSE 71: JOHN \*FINISH VISIT MARY JOHN WIL L VISIT MARY 74: \*IX \*GO \*MARY MARY TON NHOL VISIT MARY 77: \*JOHN BLAME \*LOVE ANN BLAM

E MARY

84: \*JOHN \*GIVE1 \*VISIT BOOK IX-1P FI ND SOMETHING-ONE BOOK 89: \*MARY IX \*IX \*IX IX \*ARRIVE \*BOOK JOHN IX

GIVE MAN IX NEW COAT 90: JOHN \*SOMETHING-ONE IX \*IX \*VISIT \*ARRIVE JOHN GIV E IX SOMETHING-ONE WOMAN BOOK

92: JOHN \*IX IX \*IX \*IX BOOK JOHN GIV E IX SOMETHING-ONE WOMAN BOOK 100: \*IX NEW CAR \*ARRIVE POSS NEW

105: JOHN \*FRANK JOHN LEG 107: JOHN \*IX \*HAVE \*ARRIVE \*JOHN JOHN POS

CAR BREAK-DOWN

S FRIEND HAVE CANDY	
108: *IX ARRIVE	WOMAN AR
RIVE	
113: IX CAR *IX *MARY *BOX LUE SUE BUY	IX CAR B
119: *VISIT *BUY1 IX *BOX *IX	SUE BUY
IX CAR BLUE	
122: JOHN *BUY BOOK	JOHN REA
D BOOK	701N PIN
139: JOHN *BUY1 WHAT *MARY BOOK WHAT YESTERDAY BOOK	JOHN BUY
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	
158: LOVE JOHN WHO	LOVE JOH
N WHO	JOHN TV
167: JOHN *MARY *GO LOVE MARY SAY LOVE MARY	JOHN IX
171: JOHN MARY BLAME	JOHN MAR
Y BLAME	
174: *CAR *GIVE1 GIVE1 *YESTERDAY *WHAT	PEOPLE G
ROUP GIVE1 JANA TOY 181: JOHN ARRIVE	JOHN ARR
IVE	JOHN ARK
184: *IX BOY *GIVE1 TEACHER *YESTERDAY	ALL BOY
GIVE TEACHER APPLE	
189: JOHN *SOMETHING-ONE *VISIT BOX	JOHN GIV
E GIRL BOX 193: JOHN *SOMETHING-ONE *VISIT BOX	JOHN GIV
E GIRL BOX	301114 314
199: *JOHN *ARRIVE *GO	LIKE CHO
COLATE WHO	
201: JOHN *MARY *LOVE *JOHN *GIVE1 HOUSE L MARY IX-1P BUY HOUSE	JOHN TEL
running: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <cl< td=""><td>ass 'mv model se</td></cl<>	ass 'mv model se
lectors.SelectorCV'>	7
**** UED 0.6744573033707065	
**** WER = 0.6741573033707865 Total correct: 58 out of 178	
Video Recognized	Correct
	==========
2. JOHN HITTE HOMEHODY	JOHN LIDT
2: JOHN WRITE HOMEWORK TE HOMEWORK	JOHN WRI
7: JOHN *TOY *MARY *BOX	JOHN CAN
GO CAN	
12: *LAST-WEEK *WHAT *WHAT *HOUSE	JOHN CAN
GO CAN 21: JOHN *HOMEWORK *HOMEWORK *FUTURE *CAR *PARTY *CHICAGO	*TOMORROW JOHN
FISH WONT EAT BUT CAN EAT CHICKEN	TOMORROW JOHN
25: JOHN *JOHN IX *HIT IX	JOHN LIK
E IX IX IX	
28: JOHN *HIT *HIT IX *HIT	JOHN LIK
E IX IX IX 30: JOHN *MARY *SHOOT *MARY *SHOOT	JOHN LIK
E IX IX IX	JOHN LIK
36: MARY *VISIT *SHOOT *SHOOT *MARY *IX	MARY VEG
ETABLE KNOW IX LIKE CORN1	

40: JOHN *SHOOT *VISIT *JOHN *SHOOT	JOHN IX
THINK MARY LOVE  43: JOHN *HIT BUY HOUSE  T BUY HOUSE	JOHN MUS
50: *JOHN *FUTURE BUY CAR *HOMEWORK OHN BUY CAR SHOULD	FUTURE J
54: JOHN SHOULD *MARY BUY HOUSE ULD NOT BUY HOUSE	JOHN SHO
57: *MARY *VISIT VISIT *SHOOT  IDE VISIT MARY	JOHN DEC
67: JOHN *JOHN *MARY *LAST-WEEK HOUSE URE NOT BUY HOUSE	JOHN FUT
71: JOHN *VISIT VISIT MARY L VISIT MARY	JOHN WIL
74: *SHOOT *VISIT *SHOOT *SHOOT VISIT MARY	JOHN NOT
77: *JOHN *GIVE1 *HOMEWORK E MARY	ANN BLAM
84: *HOMEWORK *HOMEWORK *POSS *WRITE ND SOMETHING-ONE BOOK	IX-1P FI
89: *MARY IX *IX *IX IX *ARRIVE *LAST-WEEK GIVE MAN IX NEW COAT	JOHN IX
90: JOHN *SHOOT *LEAVE *GIVE1 *VISIT *ARRIVE E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
92: JOHN *IX IX *IX *WRITE E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
100: *IX *WRITE CAR *WRITE CAR BREAK-DOWN	POSS NEW
105: JOHN *FRANK 107: JOHN *MARY FRIEND *LOVE *WHO	JOHN LEG JOHN POS
S FRIEND HAVE CANDY  108: *IX *HOMEWORK	WOMAN AR
RIVE 113: *SHOOT CAR *MARY *MARY *BOX LUE SUE BUY	IX CAR B
119: *VISIT *BUY1 *MARY *BOX *VISIT IX CAR BLUE	SUE BUY
122: JOHN *CHICAGO BOOK D BOOK	JOHN REA
139: JOHN *BOX WHAT *TOY *BORROW WHAT YESTERDAY BOOK	JOHN BUY
142: JOHN BUY *POSS WHAT *WRITE YESTERDAY WHAT BOOK	JOHN BUY
TESTERBITI MINTE BOOK	JOHN DOT
158: LOVE JOHN *IX N WHO	LOVE JOH
N WHO 167: JOHN IX *VISIT *WOMAN *LOVE	
N WHO	LOVE JOH
N WHO 167: JOHN IX *VISIT *WOMAN *LOVE SAY LOVE MARY 171: JOHN *JOHN *GIVE1	LOVE JOH
N WHO 167: JOHN IX *VISIT *WOMAN *LOVE SAY LOVE MARY 171: JOHN *JOHN *GIVE1 Y BLAME 174: *FRIEND GROUP GIVE1 *VISIT TOY	LOVE JOH JOHN IX JOHN MAR
N WHO 167: JOHN IX *VISIT *WOMAN *LOVE SAY LOVE MARY 171: JOHN *JOHN *GIVE1 Y BLAME 174: *FRIEND GROUP GIVE1 *VISIT TOY ROUP GIVE1 JANA TOY 181: *SHOOT *HOMEWORK	LOVE JOH  JOHN IX  JOHN MAR  PEOPLE G

193: JOHN *VISIT *VISIT BOX	JOHN GIV
E GIRL BOX 199: *JOHN *HOMEWORK *MARY COLATE WHO	LIKE CHO
201: JOHN *MARY *IX *LOVE *LAST-WEEK HOUSE L MARY IX-1P BUY HOUSE	JOHN TEL
running: ['norm-rx', 'norm-ry', 'norm-lx', 'norm-ly'] <class lectors.selectorconstant'=""></class>	'my_model_se
**** WER = 0.6235955056179775	
Total correct: 67 out of 178 Video Recognized	Correct
=======================================	
======================================	JOHN WRI
TE HOMEWORK 7: JOHN *NEW *JOHN CAN	JOHN CAN
GO CAN	JOHN CAN
12: *SHOULD *HAVE *GO1 CAN	JOHN CAN
GO CAN	JOHN ETC
21: *LIKE *NEW *HAVE *IX-1P *CAR *BLAME *CHICKEN *WRITE H WONT EAT BUT CAN EAT CHICKEN	JOHN FIS
25: *IX LIKE *LIKE *LIKE IX	JOHN LIK
E IX IX IX	701111 1 714
28: *ANN LIKE *ANN *LIKE *ANN E IX IX	JOHN LIK
30: *SHOOT LIKE *LOVE *LIKE *MARY	JOHN LIK
E IX IX IX	MADY VEC
36: *LEAVE *NOT *YESTERDAY *VISIT LIKE *JOHN ETABLE KNOW IX LIKE CORN1	MARY VEG
40: JOHN *LEAVE *FUTURE1 *VEGETABLE LOVE	JOHN IX
THINK MARY LOVE	
43: JOHN *SHOULD BUY HOUSE T BUY HOUSE	JOHN MUS
50: *FRANK *SEE *ARRIVE CAR *CAR	FUTURE J
OHN BUY CAR SHOULD	. 0.01.2
54: JOHN SHOULD *FUTURE *STUDENT HOUSE	JOHN SHO
ULD NOT BUY HOUSE	70.00 550
57: *MARY *MARY *MARY IDE VISIT MARY	JOHN DEC
67: *IX-1P FUTURE *JOHN *ARRIVE HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN WILL VISIT MARY	JOHN WIL
L VISIT MARY	JOHN NOT
74: *WOMAN *VISIT VISIT *FRANK VISIT MARY	JOHN NOT
77: *IX BLAME MARY	ANN BLAM
E MARY	
84: *IX *ARRIVE *NEW BOOK	IX-1P FI
ND SOMETHING-ONE BOOK 89: *FUTURE *THROW *JOHN *JOHN *WOMAN *BOOK *BREAK-DOWN	JOHN IX
GIVE MAN IX NEW COAT	
90: *SELF *GIVE1 IX *IX WOMAN *CHOCOLATE	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *GIVE1 IX *IX WOMAN BOOK	JOHN CTV
E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
100: POSS NEW CAR BREAK-DOWN	POSS NEW

CAR BREAK-DOWN	
105: *WHO *SEE 107: *TELL *IX *BOX *LIKE *JANA	JOHN LEG JOHN POS
S FRIEND HAVE CANDY  108: *LOVE *HOMEWORK	WOMAN AR
RIVE 113: IX CAR *IX SUE *HAVE LUE SUE BUY	IX CAR B
119: *VEGETABLE *BUY1 IX CAR *GO IX CAR BLUE	SUE BUY
122: JOHN *HOUSE *COAT D BOOK	JOHN REA
139: JOHN *BUY1 *CAR YESTERDAY BOOK WHAT YESTERDAY BOOK	JOHN BUY
142: JOHN BUY YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK	JOHN BUY
158: LOVE *MARY *CORN N WHO	LOVE JOH
167: JOHN *JOHN *SAY-1P LOVE MARY SAY LOVE MARY	JOHN IX
171: *SHOOT *JOHN BLAME Y BLAME	JOHN MAR
174: *NEW *GIVE1 GIVE1 *WHO *CAR ROUP GIVE1 JANA TOY	PEOPLE G
181: JOHN *BOX IVE	JOHN ARR
184: *IX *IX *GIVE1 TEACHER APPLE GIVE TEACHER APPLE	ALL BOY
189: *JANA *SEE *PREFER *ARRIVE	JOHN GIV
E GIRL BOX  193: JOHN *SEE *YESTERDAY BOX	JOHN GIV
E GIRL BOX 199: *JOHN CHOCOLATE *JOHN	LIKE CHO
COLATE WHO 201: JOHN *THINK *WOMAN *WOMAN *STUDENT HOUSE	JOHN TEL
<pre>L MARY IX-1P BUY HOUSErunning: ['norm-rx', 'norm-ry', 'norm-lx', 'norm-ly'] <class 'my="" lectors.selectorbic'=""></class></pre>	_model_se
**** WER = 0.6573033707865169	
Total correct: 61 out of 178  Video Recognized	Correct
=======================================	
2: JOHN WRITE *ARRIVE TE HOMEWORK	JOHN WRI
7: *SHOOT *CAR *JOHN CAN GO CAN	JOHN CAN
12: JOHN *WHAT *WHAT CAN GO CAN	JOHN CAN
21: JOHN *VIDEOTAPE *VISIT *JOHN *VISIT *CAR *CAN *GIVE1 H WONT EAT BUT CAN EAT CHICKEN	JOHN FIS
25: *ANN LIKE *MARY *LIKE *LOVE E IX IX IX	JOHN LIK
28: *ANN LIKE *LOVE *MARY *LOVE E IX IX IX	JOHN LIK
30: *IX-1P *CHOCOLATE IX *FRANK IX	JOHN LIK

E IX IX IX 36: *SHOOT VEGETABLE *GIVE3 *GIVE2 LIKE *SHOOT	MARY VEG
ETABLE KNOW IX LIKE CORN1	TIAITT VEG
40: *SHOOT *SHOOT *PREFER *VEGETABLE *SHOOT	JOHN IX
THINK MARY LOVE	
43: JOHN *MARY BUY HOUSE	JOHN MUS
T BUY HOUSE	EUTUDE 3
50: *FRANK *POSS *ARRIVE CAR *IX OHN BUY CAR SHOULD	FUTURE J
54: JOHN *FUTURE *MAN *VIDEOTAPE HOUSE	JOHN SHO
ULD NOT BUY HOUSE	55
57: *SHOOT *MARY VISIT *SHOOT	JOHN DEC
IDE VISIT MARY	
67: *SHOOT *IX NOT *ARRIVE HOUSE	JOHN FUT
URE NOT BUY HOUSE	JOHN MIT
71: JOHN *FUTURE VISIT MARY I VTSTT MARY	JOHN WIL
74: JOHN *WHO *GIVE2 *WOMAN	JOHN NOT
VISIT MARY	30
77: ANN BLAME MARY	ANN BLAM
E MARY	
84: *JOHN *ARRIVE *FUTURE BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	70.00 77
89: *FUTURE *SOMETHING-ONE *VISIT *IX IX *BOOK *BREAK-DOWN GIVE MAN IX NEW COAT	JOHN IX
90: *PREFER *NOT IX *IX *VISIT BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	301111 011
92: JOHN *FRANK *WOMAN *WOMAN WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
100: POSS NEW CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	701111 1 50
105: *WHO *POSS 107: *SHOULD POSS *BOX *MARY *TOY1	JOHN LEG JOHN POS
S FRIEND HAVE CANDY	JOHN FOS
108: *SOMETHING-ONE *HOMEWORK	WOMAN AR
RIVE	
113: IX CAR *CAR *SHOOT *BOX	IX CAR B
LUE SUE BUY	
119: *SELF *BUY1 IX CAR *FINISH	SUE BUY
IX CAR BLUE 122: JOHN *GIVE1 BOOK	JOHN REA
D BOOK	JOHN KLA
139: *SHOOT *BUY1 *VIDEOTAPE YESTERDAY BOOK	JOHN BUY
WHAT YESTERDAY BOOK	
142: *FRANK BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	
158: LOVE *MARY *CORN	LOVE JOH
N WHO 167: *SHOULD *NOT *SAY-1P LOVE *LOVE	JOHN IX
SAY LOVE MARY	30111V 17X
171: *LIKE *TOY1 BLAME	JOHN MAR
Y BLAME	
174: *VISIT *GIVE1 GIVE1 *GIVE2 *CAR	PEOPLE G
ROUP GIVE1 JANA TOY	701N 455
181: *VISIT *VIDEOTAPE IVE	JOHN ARR
184: *IX *FUTURE *GIVE1 TEACHER APPLE	ALL BOY
II. IN TOTAL STREET TENGLES AT THE	501

```
GIVE TEACHER APPLE
 189: *TOY1 *SELF *GIVE2 *ARRIVE
                                                                  JOHN GIV
E GIRL BOX
 193: *NOT *SEE *NOT BOX
                                                                  JOHN GIV
E GIRL BOX
 199: *JOHN *ARRIVE *GO
                                                                  LIKE CHO
COLATE WHO
 201: JOHN *THINK *WOMAN *LOVE *BOOK HOUSE
                                                                  JOHN TEL
L MARY IX-1P BUY HOUSE
----running: ['norm-rx', 'norm-ry', 'norm-lx', 'norm-ly'] <class 'my model se
lectors.SelectorDIC'>
**** WER = 0.5955056179775281
Total correct: 72 out of 178
Video Recognized
                                                                  Correct
______
2: JOHN WRITE *ARRIVE
                                                                  JOHN WRI
TE HOMEWORK
   7: *MARY *CAR GO CAN
                                                                  JOHN CAN
GO CAN
  12: JOHN *WHAT *ARRIVE CAN
                                                                  JOHN CAN
GO CAN
   21: *MARY *JOHN *JOHN *BLAME *CAR *CAR *FUTURE CHICKEN
                                                                  JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN
   25: JOHN LIKE IX *LIKE IX
                                                                  JOHN LIK
E IX IX IX
  28: *ANN *ANN IX *MARY IX
                                                                  JOHN LIK
E IX IX IX
  30: *IX-1P *CHOCOLATE *MARY *LOVE *LOVE
                                                                  JOHN LIK
E IX IX IX
   36: MARY *MARY *YESTERDAY *SHOOT LIKE *IX
                                                                  MARY VEG
ETABLE KNOW IX LIKE CORN1
  40: *MARY *JOHN *FUTURE1 *VEGETABLE *MARY
                                                                  JOHN IX
THINK MARY LOVE
  43: JOHN *FUTURE BUY HOUSE
                                                                  JOHN MUS
T BUY HOUSE
  50: *POSS *SEE *JOHN CAR *IX
                                                                  FUTURE J
OHN BUY CAR SHOULD
   54: JOHN *FUTURE *SHOULD *ARRIVE HOUSE
                                                                  JOHN SHO
ULD NOT BUY HOUSE
  57: *SHOOT *IX *JOHN *VISIT
                                                                  JOHN DEC
IDE VISIT MARY
  67: *MARY *IX *JOHN *ARRIVE HOUSE
                                                                  JOHN FUT
URE NOT BUY HOUSE
  71: JOHN *FUTURE VISIT MARY
                                                                  JOHN WIL
L VISIT MARY
  74: *GO *VISIT VISIT MARY
                                                                  TON NHOL
VISIT MARY
   77: ANN BLAME MARY
                                                                  ANN BLAM
E MARY
  84: *JOHN *ARRIVE *VISIT BOOK
                                                                  IX-1P FI
ND SOMETHING-ONE BOOK
  89: *MARY *POSS *IX *IX IX *ARRIVE *BREAK-DOWN
                                                                  JOHN IX
GIVE MAN IX NEW COAT
  90: *SELF *IX IX *IX WOMAN BOOK
                                                                  JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK
```

92: JOHN *IX IX *IX *LOVE BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK 100: POSS NEW CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	
105: JOHN *POSS 107: *MARY POSS *BOX *MARY *TOY1	JOHN LEG JOHN POS
S FRIEND HAVE CANDY 108: *LOVE *JOHN	WOMAN AR
RIVE	WOMAN AN
113: *SHOULD CAR *IX *JOHN *BOX	IX CAR B
LUE SUE BUY	
119: SUE *BUY1 IX *JOHN *GO	SUE BUY
IX CAR BLUE	
122: JOHN *GIVE1 BOOK	JOHN REA
D BOOK	
139: JOHN *BUY1 *CAR *JOHN BOOK	JOHN BUY
WHAT YESTERDAY BOOK	
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	
158: LOVE JOHN WHO	LOVE JOH
N WHO	
167: JOHN IX *SAY-1P LOVE *IX	JOHN IX
SAY LOVE MARY	JOHN IX
171: *MARY *JOHN BLAME	JOHN MAR
Y BLAME	JUHN MAK
	DEODLE C
174: *CAR *GIVE1 GIVE1 *YESTERDAY *CAR	PEOPLE G
ROUP GIVE1 JANA TOY	
181: JOHN *BOX	JOHN ARR
IVE	
184: *IX BOY *GIVE1 TEACHER APPLE	ALL BOY
GIVE TEACHER APPLE	
189: *MARY *MARY *YESTERDAY BOX	JOHN GIV
E GIRL BOX	
193: *LEAVE *YESTERDAY *YESTERDAY BOX	JOHN GIV
E GIRL BOX	
199: *JOHN *ARRIVE *JOHN	LIKE CHO
COLATE WHO	LIKE CHO
201: JOHN *GIVE1 *IX *WOMAN *ARRIVE HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	JOHN TEE
	m, madal sa
running: ['norm-rx', 'norm-ry', 'norm-lx', 'norm-ly'] <class '<="" td=""><td>ny_mode1_se</td></class>	ny_mode1_se
<pre>lectors.SelectorCV'&gt;</pre>	
**** WER = 0.6348314606741573	
Total correct: 65 out of 178	
Video Recognized	Correct
	=======
=======================================	
2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK	
7: JOHN *JOHN GO CAN	JOHN CAN
GO CAN	
12: *IX *CAR *WHAT CAN	JOHN CAN
GO CAN	JOHN CAN
	JOHN ETC
21: JOHN *JOHN *HOMEWORK *IX *CAR *CAR *FUTURE *BLAME	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	30UN 1711
25: *ANN *ANN *ANN *ANN	JOHN LIK
E IX IX IX	

28: *ANN *ANN *ANN *ANN	JOHN LIK
E IX IX IX 30: *IX-1P LIKE *MARY IX IX	JOHN LIK
E IX IX IX	30.11. 22.1
36: *SHOOT *SHOULD *GIVE1 *SHOOT *LEAVE *IX	MARY VEG
ETABLE KNOW IX LIKE CORN1	
40: JOHN *MARY *SEE *SHOULD *MARY	JOHN IX
THINK MARY LOVE	
43: JOHN *JOHN BUY HOUSE	JOHN MUS
T BUY HOUSE	
50: *POSS *FRANK *HOMEWORK CAR *HOMEWORK	FUTURE J
OHN BUY CAR SHOULD	
54: JOHN *JOHN *WILL *WRITE HOUSE	JOHN SHO
ULD NOT BUY HOUSE	
57: *SHOOT *GO *GO MARY	JOHN DEC
IDE VISIT MARY	
67: JOHN FUTURE *JOHN *LAST-WEEK HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN WILL *JOHN MARY	JOHN WIL
L VISIT MARY	
74: *GO NOT VISIT MARY	JOHN NOT
VISIT MARY	301114 1401
77: ANN BLAME MARY	ANN BLAM
E MARY	ANN DEAN
84: *IX *HOMEWORK *HOMEWORK *WRITE	IX-1P FI
ND SOMETHING-ONE BOOK	IV-IL II
89: *MARY IX *IX IX NEW *LAST-WEEK	JOHN IX
GIVE MAN IX NEW COAT	JOHN IX
90: *SELF *GIVE1 *SOMETHING-ONE SOMETHING-ONE WOMAN *BORROW	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
92: JOHN *IX IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
100: POSS *WRITE CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	FU33 INLW
105: JOHN *POSS	JOHN LEG
107: *MARY *IX FRIEND *JOHN *JOHN	JOHN POS
S FRIEND HAVE CANDY	LIOMANI AB
108: *TOMORROW *LOVE	WOMAN AR
RIVE	TV CAR R
113: *HIT CAR *IX *JOHN *HOMEWORK	IX CAR B
LUE SUE BUY	CHE DIN
119: *MARY *BUY1 *HOMEWORK *JOHN *IX	SUE BUY
IX CAR BLUE	JOHN DEA
122: JOHN *GIVE1 BOOK	JOHN REA
D BOOK	JOHN BUY
139: JOHN *HOMEWORK *CAR *GO *LOVE	JOHN BUY
WHAT YESTERDAY BOOK	JOHN BUY
142: JOHN *ARRIVE *POSS WHAT *BREAK-DOWN	JOHN BUY
YESTERDAY WHAT BOOK	10//5 70//
158: LOVE JOHN *CORN	LOVE JOH
N WHO	701M TV
167: JOHN *GIVE2 *MARY LOVE *JOHN	JOHN IX
SAY LOVE MARY	701"
171: JOHN *JOHN BLAME	JOHN MAR
Y BLAME	
	DEODLE C
174: *CAR GROUP GIVE1 *VISIT TOY ROUP GIVE1 JANA TOY	PEOPLE G

181: *MARY *JOHN	JOHN ARR
IVE 184: *IX *WHO *GIVE1 TEACHER *VISIT	ALL BOY
GIVE TEACHER APPLE	ALL DOT
189: *TOY1 *MARY *FINISH *HOMEWORK	JOHN GIV
E GIRL BOX 193: JOHN *YESTERDAY *GO BOX	JOHN GIV
E GIRL BOX	JOHN GIV
199: *JOHN *ARRIVE *JOHN	LIKE CHO
COLATE WHO 201: JOHN *GIVE1 *IX *WOMAN *WRITE HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	JOHN TEE
running: ['polar-rr', 'polar-rtheta', 'polar-lr', 'polar-ltheta'	] <class< td=""></class<>
<pre>'my_model_selectors.SelectorConstant'&gt;</pre>	
**** WER = 0.6179775280898876	
Total correct: 68 out of 178	
Video Recognized	Correct
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2: *GO WRITE HOMEWORK	JOHN WRI
TE HOMEWORK	
7: JOHN *WHAT *MARY *WHAT GO CAN	JOHN CAN
12: JOHN *WHAT *GO1 CAN	JOHN CAN
GO CAN	
21: *IX *HOMEWORK WONT *FUTURE *CAR *CAR *GO *TOMORROW	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN 25: *FRANK LIKE IX *WHO IX	JOHN LIK
E IX IX IX	JOIN LIK
28: *IX *WHO *FUTURE *FUTURE IX	JOHN LIK
E IX IX IX 30: *SHOULD LIKE *GO *MARY *GO	JOHN LIK
E IX IX IX	JOHN LIK
36: *SOMETHING-ONE VEGETABLE *GIRL *GIVE *MARY *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1  40: *SUE *GIVE *DECIDE MARY *GO	JOHN IX
THINK MARY LOVE	JUNI IX
43: *IX *GO BUY HOUSE	JOHN MUS
T BUY HOUSE	FUTURE 3
50: *POSS *SEE BUY CAR *ARRIVE OHN BUY CAR SHOULD	FUTURE J
54: JOHN SHOULD *WHO BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	701N DEC
57: *MARY *PREFER *MARY MARY  IDE VISIT MARY	JOHN DEC
67: *LIKE *MOTHER NOT BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN *FINISH *GIVE1 MARY L VISIT MARY	JOHN WIL
74: *GO *WHO *GO *GO	JOHN NOT
VISIT MARY	
77: *IX BLAME *LOVE E MARY	ANN BLAM
84: *HOMEWORK *GIVE1 *POSS BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	
89: *MAN *GIVE *WOMAN *IX IX *BUY *BOOK	JOHN IX

CTUE MAN TV NEU COAT	
GIVE MAN IX NEW COAT 90: JOHN *GIVE1 IX *GIVE3 *GIVE1 *COAT	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
92: JOHN *WOMAN *WOMAN WOMAN BOOK E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
100: POSS NEW CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	
<pre>105: *FRANK *VEGETABLE 107: *LIKE *SOMETHING-ONE *HAVE *GO *WHO</pre>	JOHN LEG JOHN POS
S FRIEND HAVE CANDY	JOHN POS
108: *IX ARRIVE	WOMAN AR
RIVE 113: IX CAR *SUE *SOMETHING-ONE *ARRIVE	IX CAR B
LUE SUE BUY	IX CAN D
119: *PREFER *BUY1 IX CAR *SOMETHING-ONE	SUE BUY
IX CAR BLUE 122: JOHN *GIVE1 BOOK	JOHN REA
D BOOK	JOHN KLA
139: *SHOULD *BUY1 *CAR YESTERDAY BOOK	JOHN BUY
WHAT YESTERDAY BOOK	JOHN DHV
142: *FRANK BUY YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK	JOHN BUY
158: LOVE *MARY WHO	LOVE JOH
N WHO	JOHN TV
167: *MARY *SOMETHING-ONE *MARY LOVE *LOVE SAY LOVE MARY	JOHN IX
171: *SOMETHING-ONE *SOMETHING-ONE BLAME	JOHN MAR
Y BLAME	DEODLE C
174: *CAN *GIVE3 GIVE1 *GO *WHAT ROUP GIVE1 JANA TOY	PEOPLE G
181: *SUE ARRIVE	JOHN ARR
IVE	ALL BOY
184: *IX BOY *GIVE1 TEACHER APPLE GIVE TEACHER APPLE	ALL BOY
189: *SUE *SOMETHING-ONE *YESTERDAY *ARRIVE	JOHN GIV
E GIRL BOX	JOHN CTV
193: JOHN *SOMETHING-ONE *YESTERDAY BOX E GIRL BOX	JOHN GIV
199: *HOMEWORK CHOCOLATE WHO	LIKE CHO
COLATE WHO	
201: JOHN *MAN *MAN *JOHN BUY HOUSE L MARY IX-1P BUY HOUSE	JOHN TEL
running: ['polar-rr', 'polar-rtheta', 'polar-lr', 'polar-ltheta 'my_model_selectors.SelectorBIC'>	'] <class< td=""></class<>
**** WER = 0.601123595505618  Total correct: 71 out of 178	
Video Recognized	Correct
	=======
2: *WHO *BOOK *GO	JOHN WRI
TE HOMEWORK	
7: JOHN CAN *JOHN *WHAT	JOHN CAN
GO CAN 12: JOHN *WHAT *WHAT CAN	JOHN CAN
GO CAN	
21: *FRANK *NEW *CAR *PREFER *GIVE1 *GIVE1 EAT *FUTURE	JOHN FIS

LI LIGHT FAT DUT CAN FAT CUTCKEN	
H WONT EAT BUT CAN EAT CHICKEN 25: JOHN LIKE *MARY *LIKE *LOVE	JOHN LIK
E IX IX IX	JOHN LIK
28: JOHN *WHO *MARY *MARY *LOVE	JOHN LIK
E IX IX IX	
30: *SHOULD LIKE *MARY *LIKE IX	JOHN LIK
E IX IX IX	MADY 1/56
36: MARY VEGETABLE *GIVE *GIVE *BILL *MARY ETABLE KNOW IX LIKE CORN1	MARY VEG
40: *MARY *BILL *GIVE *BILL *MARY	JOHN IX
THINK MARY LOVE	
43: JOHN *SHOULD BUY HOUSE	JOHN MUS
T BUY HOUSE	
50: *FRANK *SEE BUY CAR *JOHN	FUTURE J
OHN BUY CAR SHOULD 54: JOHN *GIVE NOT BUY HOUSE	JOHN CHO
ULD NOT BUY HOUSE	JOHN SHO
57: *MARY *VEGETABLE *WOMAN MARY	JOHN DEC
IDE VISIT MARY	
67: *POSS FUTURE *MARY BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN *FUTURE *GO *WOMAN	JOHN WIL
L VISIT MARY 74: *MARY *BILL *BILL MARY	JOHN NOT
VISIT MARY	JOHN NOT
77: *JOHN *MARY *LOVE	ANN BLAM
E MARY	
84: *LOVE *ARRIVE *YESTERDAY BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	70UN TV
89: *GIVE *GIVE *IX *IX IX *ARRIVE *BOOK GIVE MAN IX NEW COAT	JOHN IX
90: *SOMETHING-ONE *GIVE1 IX *IX *GIVE1 BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	301111 011
92: JOHN *WOMAN IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
100: POSS NEW CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	70UN 150
105: JOHN *POSS 107: *SHOULD POSS *ARRIVE HAVE *WHO	JOHN LEG JOHN POS
S FRIEND HAVE CANDY	JOHN POS
108: WOMAN *LOVE	WOMAN AR
RIVE	
113: IX CAR BLUE SUE *ARRIVE	IX CAR B
LUE SUE BUY	CUE DIN
119: *VEGETABLE *BUY1 *BLUE *BLAME *SEE IX CAR BLUE	SUE BUY
122: JOHN *GIVE1 BOOK	JOHN REA
D BOOK	JOHN HEA
139: *SHOULD *BOOK *CAR YESTERDAY BOOK	JOHN BUY
WHAT YESTERDAY BOOK	
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK 158: LOVE *MARY WHO	LOVE TOU
N WHO	LOVE JOH
167: *MARY *SUE *BILL LOVE *LOVE	JOHN IX
SAY LOVE MARY	
171: *SUE *SUE BLAME	JOHN MAR

```
Y BLAME
 174: *GIVE1 *GIVE1 GIVE1 *EAT *WHAT
                                                                  PEOPLE G
ROUP GIVE1 JANA TOY
 181: *SUE ARRIVE
                                                                  JOHN ARR
IVE
 184: *IX BOY *GIVE1 TEACHER *GIVE
                                                                  ALL BOY
GIVE TEACHER APPLE
 189: JOHN *SEE *SEE *ARRIVE
                                                                  JOHN GIV
E GIRL BOX
 193: JOHN *SOMETHING-ONE *GIVE1 BOX
                                                                  JOHN GIV
E GIRL BOX
 199: *LOVE *STUDENT WHO
                                                                  LIKE CHO
COLATE WHO
 201: JOHN *GIVE *WOMAN *JOHN BUY HOUSE
                                                                  JOHN TEL
L MARY IX-1P BUY HOUSE
----running: ['polar-rr', 'polar-rtheta', 'polar-lr', 'polar-ltheta'] <class
 'my model selectors.SelectorDIC'>
**** WER = 0.5449438202247191
Total correct: 81 out of 178
Video Recognized
                                                                  Correct
______
_____
   2: JOHN *NEW *GIVE1
                                                                  JOHN WRI
TE HOMEWORK
   7: JOHN CAN GO CAN
                                                                  JOHN CAN
GO CAN
  12: JOHN *WHAT *JOHN CAN
                                                                  JOHN CAN
GO CAN
   21: JOHN *NEW *JOHN *PREFER *GIVE1 *WHAT *FUTURE *WHO
                                                                  JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN
  25: JOHN *IX IX *WHO IX
                                                                  JOHN LIK
E IX IX IX
  28: JOHN *FUTURE IX *FUTURE *LOVE
                                                                  JOHN LIK
E IX IX IX
   30: JOHN LIKE *MARY *MARY *MARY
                                                                  JOHN LIK
E IX IX IX
   36: *IX *VISIT *GIVE *GIVE *MARY *MARY
                                                                  MARY VEG
ETABLE KNOW IX LIKE CORN1
  40: JOHN *GO *GIVE *JOHN *MARY
                                                                  JOHN IX
THINK MARY LOVE
  43: JOHN *IX BUY HOUSE
                                                                  JOHN MUS
T BUY HOUSE
  50: *JOHN *SEE BUY CAR *JOHN
                                                                  FUTURE J
OHN BUY CAR SHOULD
  54: JOHN SHOULD NOT BUY HOUSE
                                                                  JOHN SHO
ULD NOT BUY HOUSE
  57: *MARY *GO *GO MARY
                                                                  JOHN DEC
IDE VISIT MARY
  67: *SHOULD FUTURE *MARY BUY HOUSE
                                                                  JOHN FUT
URE NOT BUY HOUSE
  71: JOHN *FUTURE *GIVE1 MARY
                                                                  JOHN WIL
L VISIT MARY
  74: *IX *GO *GO *VISIT
                                                                  JOHN NOT
VISIT MARY
  77: *JOHN *GIVE1 MARY
                                                                  ANN BLAM
E MARY
```

84: *HOMEWORK *GIVE1 *GIVE1 *COAT ND SOMETHING-ONE BOOK	IX-1P FI
89: *GIVE *WOMAN *WOMAN IX *ARRIVE *BOOK GIVE MAN IX NEW COAT	JOHN IX
90: JOHN GIVE IX SOMETHING-ONE WOMAN *ARRIVE E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
92: JOHN *WOMAN IX *WOMAN WOMAN BOOK E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
100: POSS NEW CAR BREAK-DOWN CAR BREAK-DOWN	POSS NEW
105: JOHN *SEE 107: JOHN POSS *HAVE HAVE *MARY	JOHN LEG JOHN POS
S FRIEND HAVE CANDY 108: *LOVE *LOVE	WOMAN AR
RIVE	
113: IX CAR *IX *MARY *JOHN LUE SUE BUY	IX CAR B
119: *MARY *BUY1 IX *BLAME *IX IX CAR BLUE	SUE BUY
122: JOHN *GIVE1 BOOK	JOHN REA
D BOOK  139: JOHN *ARRIVE WHAT *MARY *ARRIVE	JOHN BUY
WHAT YESTERDAY BOOK 142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	
158: LOVE JOHN WHO	LOVE JOH
N WHO  167: JOHN *MARY *VISIT LOVE MARY	JOHN IX
SAY LOVE MARY 171: *IX MARY BLAME	JOHN MAR
Y BLAME	
174: *JOHN *JOHN GIVE1 *YESTERDAY *JOHN	PEOPLE G
ROUP GIVE1 JANA TOY	
181: *EAT ARRIVE	JOHN ARR
IVE	
184: *GO BOY *GIVE1 TEACHER *YESTERDAY	ALL BOY
GIVE TEACHER APPLE	JOHN CTV
189: *MARY *GO *YESTERDAY BOX	JOHN GIV
E GIRL BOX 193: JOHN *GO *YESTERDAY BOX	JOHN CTV
E GIRL BOX	JOHN GIV
199: *JOHN *STUDENT *GO	LIKE CHO
COLATE WHO	LIKE CHO
201: JOHN *MAN *LOVE *JOHN BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	
running: ['polar-rr', 'polar-rtheta', 'polar-lr', 'polar-ltheta'	l <class< td=""></class<>
'my_model_selectors.SelectorCV'>	
**** WER = 0.5730337078651685	
Total correct: 76 out of 178	
Video Recognized	Correct
======================================	
=======================================	
2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK	
7: JOHN *TOY GO CAN	JOHN CAN
GO CAN	

12: JOHN *MANY *GIVE1 CAN	JOHN CAN
GO CAN 21: JOHN *NEW *HOMEWORK *FUTURE *BUY *WHAT *CHICAGO *WHO	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN 25: *MARY *MARY IX *MARY IX	JOHN LIK
E IX IX IX	70UN 1 TV
28: JOHN *MARY *MARY *LOVE E IX IX	JOHN LIK
30: JOHN *MARY *MARY IX F TX TX TX	JOHN LIK
36: MARY *OLD *GO *GIVE2 *MARY *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1  40: JOHN *GO *APPLE *SAY-1P *MARY	JOHN IX
THINK MARY LOVE	
43: JOHN *HIT BUY HOUSE	JOHN MUS
T BUY HOUSE	CUTURE 7
50: *MARY *SEE BUY CAR *HOMEWORK OHN BUY CAR SHOULD	FUTURE J
54: JOHN SHOULD NOT BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	JOHN JHO
57: *MARY *OLD *GO MARY	JOHN DEC
IDE VISIT MARY	
67: JOHN FUTURE *WHO BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE 71: JOHN *VISIT *CHICAGO MARY	JOHN WIL
L VISIT MARY	
74: JOHN *GO *GO *VISIT VISIT MARY	JOHN NOT
77: *JOHN BLAME MARY	ANN BLAM
E MARY  84: *HOMEWORK *WRITE *HOMEWORK *WRITE	IX-1P FI
ND SOMETHING-ONE BOOK	
ND SOMETHING-ONE BOOK 89: *MARY IX *WOMAN *IX IX *ARRIVE *BOOK	JOHN IX
89: *MARY IX *WOMAN *IX IX *ARRIVE *BOOK GIVE MAN IX NEW COAT 90: JOHN *SOMETHING-ONE *SOMETHING-ONE SOMETHING-ONE WOMAN *ARRIV	JOHN IX
89: *MARY IX *WOMAN *IX IX *ARRIVE *BOOK GIVE MAN IX NEW COAT 90: JOHN *SOMETHING-ONE *SOMETHING-ONE SOMETHING-ONE WOMAN *ARRIV IVE IX SOMETHING-ONE WOMAN BOOK 92: JOHN *WOMAN IX *IX *IX BOOK	JOHN IX
89: *MARY IX *WOMAN *IX IX *ARRIVE *BOOK GIVE MAN IX NEW COAT 90: JOHN *SOMETHING-ONE *SOMETHING-ONE SOMETHING-ONE WOMAN *ARRIV IVE IX SOMETHING-ONE WOMAN BOOK 92: JOHN *WOMAN IX *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK	JOHN IX /E JOHN G JOHN GIV
89: *MARY IX *WOMAN *IX IX *ARRIVE *BOOK GIVE MAN IX NEW COAT 90: JOHN *SOMETHING-ONE *SOMETHING-ONE SOMETHING-ONE WOMAN *ARRIV IVE IX SOMETHING-ONE WOMAN BOOK 92: JOHN *WOMAN IX *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: POSS *WRITE CAR BREAK-DOWN	JOHN IX /E JOHN G
89: *MARY IX *WOMAN *IX IX *ARRIVE *BOOK GIVE MAN IX NEW COAT 90: JOHN *SOMETHING-ONE *SOMETHING-ONE SOMETHING-ONE WOMAN *ARRIV IVE IX SOMETHING-ONE WOMAN BOOK 92: JOHN *WOMAN IX *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: POSS *WRITE CAR BREAK-DOWN CAR BREAK-DOWN	JOHN IX /E JOHN G JOHN GIV POSS NEW
89: *MARY IX *WOMAN *IX IX *ARRIVE *BOOK GIVE MAN IX NEW COAT 90: JOHN *SOMETHING-ONE *SOMETHING-ONE SOMETHING-ONE WOMAN *ARRIV IVE IX SOMETHING-ONE WOMAN BOOK 92: JOHN *WOMAN IX *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: POSS *WRITE CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *SEE	JOHN IX /E JOHN G JOHN GIV POSS NEW JOHN LEG
89: *MARY IX *WOMAN *IX IX *ARRIVE *BOOK GIVE MAN IX NEW COAT 90: JOHN *SOMETHING-ONE *SOMETHING-ONE SOMETHING-ONE WOMAN *ARRIV IVE IX SOMETHING-ONE WOMAN BOOK 92: JOHN *WOMAN IX *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: POSS *WRITE CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *SEE 107: JOHN *MARY *LIVE *LOVE CANDY	JOHN IX /E JOHN G JOHN GIV POSS NEW
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89: *MARY IX *WOMAN *IX IX *ARRIVE *BOOK GIVE MAN IX NEW COAT  90: JOHN *SOMETHING-ONE *SOMETHING-ONE SOMETHING-ONE WOMAN *ARRIVIVE IX SOMETHING-ONE WOMAN BOOK  92: JOHN *WOMAN IX *IX *IX BOOK  E IX SOMETHING-ONE WOMAN BOOK  100: POSS *WRITE CAR BREAK-DOWN  CAR BREAK-DOWN  105: JOHN *SEE  107: JOHN *MARY *LIVE *LOVE CANDY  S FRIEND HAVE CANDY  108: WOMAN *BOOK  RIVE  113: *JOHN *TOY *MARY *IX *BOX  LUE SUE BUY  119: *OLD *LAST-WEEK *MARY *TOY *SAY-1P  IX CAR BLUE  122: JOHN *CAR BOOK  D BOOK  139: JOHN *LAST-WEEK WHAT *MARY *LAST-WEEK  WHAT YESTERDAY BOOK  142: JOHN BUY YESTERDAY WHAT BOOK  YESTERDAY WHAT BOOK	JOHN IX  /E JOHN G  JOHN GIV  POSS NEW  JOHN LEG JOHN POS  WOMAN AR  IX CAR B  SUE BUY  JOHN REA  JOHN BUY  JOHN BUY
89: *MARY IX *WOMAN *IX IX *ARRIVE *BOOK GIVE MAN IX NEW COAT  90: JOHN *SOMETHING-ONE *SOMETHING-ONE SOMETHING-ONE WOMAN *ARRIVIVE IX SOMETHING-ONE WOMAN BOOK  92: JOHN *WOMAN IX *IX *IX BOOK  E IX SOMETHING-ONE WOMAN BOOK  100: POSS *WRITE CAR BREAK-DOWN  CAR BREAK-DOWN  105: JOHN *SEE  107: JOHN *MARY *LIVE *LOVE CANDY  S FRIEND HAVE CANDY  108: WOMAN *BOOK  RIVE  113: *JOHN *TOY *MARY *IX *BOX  LUE SUE BUY  119: *OLD *LAST-WEEK *MARY *TOY *SAY-1P  IX CAR BLUE  122: JOHN *CAR BOOK  D BOOK  139: JOHN *LAST-WEEK WHAT *MARY *LAST-WEEK  WHAT YESTERDAY BOOK  142: JOHN BUY YESTERDAY WHAT BOOK	JOHN IX /E JOHN G JOHN GIV POSS NEW JOHN LEG JOHN POS WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY

167: JOHN IX *SAY-1P *PUTASIDE *LOVE	JOHN IX
SAY LOVE MARY 171: JOHN MARY *THROW	JOHN MAR
Y BLAME 174: *CAN GROUP GIVE1 *GO TOY	PEOPLE G
ROUP GIVE1 JANA TOY	
181: *YESTERDAY *HOMEWORK IVE	JOHN ARR
184: *SOMETHING-ONE *GO *JOHN TEACHER *GO GIVE TEACHER APPLE	ALL BOY
189: JOHN *JOHN *YESTERDAY BOX	JOHN GIV
E GIRL BOX 193: JOHN *HAVE *YESTERDAY BOX E GIRL BOX	JOHN GIV
199: *JOHN *HOMEWORK *IX	LIKE CHO
COLATE WHO 201: JOHN *MARY *WOMAN *JOHN *WRITE HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	JOHN IEL
<pre>running: ['delta-rx', 'delta-ry', 'delta-lx', 'delta-ly'] <class l_selectors.selectorconstant'=""></class></pre>	'my_mode
**** WER = 0.6404494382022472	
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2: JOHN *JOHN HOMEWORK TE HOMEWORK	JOHN WRI
7: JOHN *HAVE *GIVE1 *TEACHER	JOHN CAN
GO CAN  12: JOHN CAN *GO1 CAN	JOHN CAN
GO CAN 21: *MARY *MARY *JOHN *MARY *CAR *GO *FUTURE *MARY	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	
25: JOHN *MARY *JOHN IX *MARY E IX IX IX	JOHN LIK
28: JOHN *MARY *MARY IX IX E IX IX IX	JOHN LIK
30: JOHN *MARY *JOHN *JOHN IX	JOHN LIK
E IX IX IX 36: MARY *JOHN *JOHN IX *MARY *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1	
40: *MARY IX *MARY MARY *MARY THINK MARY LOVE	JOHN IX
43: JOHN *JOHN *FINISH HOUSE T BUY HOUSE	JOHN MUS
50: *JOHN JOHN BUY CAR *MARY OHN BUY CAR SHOULD	FUTURE J
54: JOHN *MARY *MARY BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE 57: JOHN *JOHN *IX *JOHN	JOHN DEC
IDE VISIT MARY 67: JOHN *JOHN BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE 71: JOHN *JOHN VISIT MARY	JOHN WIL
L VISIT MARY	
74: JOHN *JOHN *MARY MARY	JOHN NOT

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Video Recognized	Correct
**** WER = 0.6404494382022472 Total correct: 64 out of 178	
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201: JOHN *MARY MARY *LIKE *VISIT HOUSE	JOHN TEL
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199: *JOHN *ARRIVE *MARY	LIKE CHO
E GIRL BOX	JOIN GIV
193: JOHN *IX *IX BOX	JOHN GIV
189: JOHN *IX *MARY *VISIT E GIRL BOX	JOHN GIV
GIVE TEACHER APPLE	JOHN CTV
184: *IX *WHO *GIVE1 *HAVE *MARY	ALL BOY
IVE	
181: JOHN *GIVE1	JOHN ARR
ROUP GIVE1 JANA TOY	
174: *GIVE1 *MARY GIVE1 *MARY *FINISH	PEOPLE G
171: JOHN *JOHN BLAME Y BLAME	JOHN MAR
SAY LOVE MARY	JOHN MAD
167: *MARY *MARY *IX *ARRIVE *WHAT	JOHN IX
N WHO	
158: *BOY *WHO *MARY	LOVE JOH
YESTERDAY WHAT BOOK	
142: JOHN BUY *MARY *MARY *YESTERDAY	JOHN BUY
WHAT YESTERDAY BOOK	JOHN DUT
D BOOK 139: JOHN *BUY1 WHAT *MARY *ARRIVE	JOHN BUY
122: JOHN *VISIT *YESTERDAY	JOHN REA
IX CAR BLUE	JOLINI DEA
119: *JOHN *BUY1 IX CAR *IX	SUE BUY
LUE SUE BUY	CHE STO
113: *JOHN CAR *MARY *MARY *GIVE1	IX CAR B
RIVE	
108: *JOHN ARRIVE	WOMAN AR
S FRIEND HAVE CANDY	
107: JOHN POSS FRIEND *LOVE *MARY	JOHN POS
CAR BREAK-DOWN 105: JOHN *MARY	JOHN LEG
100: *JOHN NEW *WHAT BREAK-DOWN	POSS NEW
E IX SOMETHING-ONE WOMAN BOOK	חסככ אידיי
92: JOHN *MARY *JOHN *JOHN WOMAN *ARRIVE	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
90: *MARY *JOHN *JOHN *IX *IX *MARY	JOHN GIV
GIVE MAN IX NEW COAT	
89: *GIVE1 *JOHN *IX *JOHN IX *WHAT *HOUSE	JOHN IX
84: *JOHN *GO *IX *WHAT ND SOMETHING-ONE BOOK	IX-1P FI
E MARY	TV 4D FT
77: *JOHN BLAME MARY	ANN BLAM
VISIT MARY	

2: JOHN \*JOHN \*CHOCOLATE

TE HOMELIODY	
TE HOMEWORK 7: JOHN *VISIT *GIVE1 *BOOK	JOHN CAN
GO CAN	
12: JOHN *BOX *GIVE1 CAN GO CAN	JOHN CAN
21: *IX *IX *JOHN *BOOK *CAR *VISIT *MARY *MARY	JOHN FIS
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28: JOHN *BROCCOLI *GIVE IX IX E IX IX IX	JOHN LIK
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36: MARY *JOHN *JOHN IX *MARY *JOHN	MARY VEG
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40: JOHN IX *GIRL MARY *MARY THINK MARY LOVE	JOHN IX
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T BUY HOUSE	
50: *JOHN *MARY BUY CAR *MARY	FUTURE J
OHN BUY CAR SHOULD	701111 6110
54: JOHN *JOHN *WHO BUY HOUSE ULD NOT BUY HOUSE	JOHN SHO
57: JOHN *MARY *IX *JOHN	JOHN DEC
IDE VISIT MARY	301111 520
67: JOHN *JOHN *MARY *POSS HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN *JOHN VISIT *BOOK	JOHN WIL
L VISIT MARY 74: JOHN *JOHN *IX *IX	JOHN NOT
VISIT MARY	301111 1101
77: *JOHN *ARRIVE MARY	ANN BLAM
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ND SOMETHING-ONE BOOK 89: JOHN *JOHN *IX *JOHN IX *WHAT *HOUSE	JOHN IX
GIVE MAN IX NEW COAT	JOHN IX
90: *MARY *JOHN *JOHN *IX *IX *MARY	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
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100: *IX *GIVE1 *WHAT BREAK-DOWN  CAR BREAK-DOWN	POSS NEW
105: JOHN *JOHN	JOHN LEG
107: JOHN *IX *BOOK *IX *MARY	JOHN POS
S FRIEND HAVE CANDY	
108: *JOHN *BOOK	WOMAN AR
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113: *JOHN CAR *MARY *MARY *GIVE1 LUE SUE BUY 119: *JOHN *GIVE1 IX CAR *MARY IX CAR BLUE 122: JOHN *IX BOOK	IX CAR B
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N WHO  167: JOHN IX *IX *BOOK *BOOK  SAY LOVE MARY  171: JOHN *JOHN *GIVE1  Y BLAME  174: *GIVE1 *MARY GIVE1 *MARY *BOOK  ROUP GIVE1 JANA TOY  181: JOHN ARRIVE  JOUND IVE  184: *IX *WHO *GIVE1 TEACHER *MARY  GIVE TEACHER APPLE	HN HN OPL HN	JOH IX MAR LE G
167: JOHN IX *IX *BOOK *BOOK  SAY LOVE MARY  171: JOHN *JOHN *GIVE1  Y BLAME  174: *GIVE1 *MARY GIVE1 *MARY *BOOK  ROUP GIVE1 JANA TOY  181: JOHN ARRIVE  JOUNE  184: *IX *WHO *GIVE1 TEACHER *MARY  GIVE TEACHER APPLE  189: JOHN *IX *WHAT *ARRIVE	HN OPL HN	MAR
171: JOHN *JOHN *GIVE1 Y BLAME 174: *GIVE1 *MARY GIVE1 *MARY *BOOK ROUP GIVE1 JANA TOY 181: JOHN ARRIVE JO IVE 184: *IX *WHO *GIVE1 TEACHER *MARY GIVE TEACHER APPLE 189: JOHN *IX *WHAT *ARRIVE JO	OPL HN	
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	HN	CAN
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GO CAN 21: JOHN *MARY *LOVE *MARY *HOUSE *FUTURE *FUTURE *MARY JO	HN	FIS
GO CAN  21: JOHN *MARY *LOVE *MARY *HOUSE *FUTURE *FUTURE *MARY  H WONT EAT BUT CAN EAT CHICKEN  25: JOHN *IX *JOHN IX IX  JO		FIS LIK
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GO CAN  21: JOHN *MARY *LOVE *MARY *HOUSE *FUTURE *FUTURE *MARY  H WONT EAT BUT CAN EAT CHICKEN  25: JOHN *IX *JOHN IX IX  E IX IX IX  28: JOHN *MARY *JOHN IX *SHOULD  E IX IX IX  30: JOHN *IX *SHOULD *JOHN IX  JO	HN HN	LIK
GO CAN  21: JOHN *MARY *LOVE *MARY *HOUSE *FUTURE *FUTURE *MARY  H WONT EAT BUT CAN EAT CHICKEN  25: JOHN *IX *JOHN IX IX  E IX IX IX  28: JOHN *MARY *JOHN IX *SHOULD  E IX IX IX  30: JOHN *IX *SHOULD *JOHN IX  E IX IX IX  36: *JOHN *JOHN *JOHN IX *MARY *MARY  MA	HN HN HN	LIK LIK
GO CAN  21: JOHN *MARY *LOVE *MARY *HOUSE *FUTURE *FUTURE *MARY  H WONT EAT BUT CAN EAT CHICKEN  25: JOHN *IX *JOHN IX IX  E IX IX IX  28: JOHN *MARY *JOHN IX *SHOULD  E IX IX IX  30: JOHN *IX *SHOULD *JOHN IX  E IX IX IX  36: *JOHN *JOHN *JOHN IX *MARY *MARY  ETABLE KNOW IX LIKE CORN1	HN HN HN RY	LIK LIK LIK
GO CAN  21: JOHN *MARY *LOVE *MARY *HOUSE *FUTURE *FUTURE *MARY  H WONT EAT BUT CAN EAT CHICKEN  25: JOHN *IX *JOHN IX IX  E IX IX IX  28: JOHN *MARY *JOHN IX *SHOULD  E IX IX IX  30: JOHN *IX *SHOULD *JOHN IX  E IX IX IX  36: *JOHN *JOHN *JOHN IX *MARY *MARY  ETABLE KNOW IX LIKE CORN1  40: *MARY IX *JOHN MARY *MARY  THINK MARY LOVE	HN HN HN RY	LIK LIK LIK VEG
GO CAN  21: JOHN *MARY *LOVE *MARY *HOUSE *FUTURE *FUTURE *MARY  H WONT EAT BUT CAN EAT CHICKEN  25: JOHN *IX *JOHN IX IX  E IX IX IX  28: JOHN *MARY *JOHN IX *SHOULD  E IX IX IX  30: JOHN *IX *SHOULD *JOHN IX  E IX IX IX  36: *JOHN *JOHN *JOHN IX *MARY *MARY  ETABLE KNOW IX LIKE CORN1  40: *MARY IX *JOHN MARY *MARY  THINK MARY LOVE  43: JOHN *IX BUY HOUSE  T BUY HOUSE	HN HN HN RY HN	LIK LIK LIK VEG
GO CAN 21: JOHN *MARY *LOVE *MARY *HOUSE *FUTURE *FUTURE *MARY  H WONT EAT BUT CAN EAT CHICKEN 25: JOHN *IX *JOHN IX IX  E IX IX IX 28: JOHN *MARY *JOHN IX *SHOULD  E IX IX IX 30: JOHN *IX *SHOULD *JOHN IX  E IX IX IX 36: *JOHN *JOHN *JOHN IX *MARY *MARY  ### ETABLE KNOW IX LIKE CORN1 40: *MARY IX *JOHN MARY *MARY  THINK MARY LOVE 43: JOHN *IX BUY HOUSE  T BUY HOUSE 50: *JOHN JOHN BUY CAR *MARY  OHN BUY CAR SHOULD	HN HN RY HN TUR	LIK LIK LIK VEG IX MUS
GO CAN  21: JOHN *MARY *LOVE *MARY *HOUSE *FUTURE *FUTURE *MARY  H WONT EAT BUT CAN EAT CHICKEN  25: JOHN *IX *JOHN IX IX  E IX IX IX  28: JOHN *MARY *JOHN IX *SHOULD  E IX IX IX  30: JOHN *IX *SHOULD *JOHN IX  E IX IX IX  36: *JOHN *JOHN *JOHN IX *MARY *MARY  ETABLE KNOW IX LIKE CORN1  40: *MARY IX *JOHN MARY *MARY  THINK MARY LOVE  43: JOHN *IX BUY HOUSE  T BUY HOUSE  50: *JOHN JOHN BUY CAR *MARY  OHN BUY CAR SHOULD  54: JOHN *JOHN *JOHN BUY HOUSE  JOULD NOT BUY HOUSE	HN HN RY HN HN TUR	LIK LIK VEG IX MUS RE J SHO
GO CAN	HN HN RY HN HN HN HN	LIK LIK VEG IX MUS

71: JOHN *MARY VISIT MARY	JOHN WIL
L VISIT MARY 74: JOHN *JOHN *IX MARY	JOHN NOT
VISIT MARY 77: *JOHN *ARRIVE MARY	ANN BLAM
E MARY	ANN DEAT
84: *GO *CAR *IX *LOVE ND SOMETHING-ONE BOOK	IX-1P FI
89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN	JOHN IX
GIVE MAN IX NEW COAT 90: JOHN *JOHN *IX *IX *MARY	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
92: JOHN *IX *JOHN *IX WOMAN *MARY E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
	DOCC NEU
100: *JOHN *ARRIVE CAR *HOUSE	POSS NEW
CAR BREAK-DOWN	
105: JOHN *JOHN	JOHN LEG
107: JOHN POSS *ARRIVE *MARY *JOHN	JOHN POS
S FRIEND HAVE CANDY	
108: *JOHN *LOVE	WOMAN AR
RIVE	
113: *JOHN CAR *MARY *IX *GIVE1	IX CAR B
LUE SUE BUY	271 67111 2
119: *JOHN *GIVE1 IX CAR *MARY	SUE BUY
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IX CAR BLUE	JOHN DEA
122: JOHN *GIVE1 *WHAT	JOHN REA
D BOOK	
139: JOHN *GIVE1 WHAT *JOHN *WHAT	JOHN BUY
WHAT YESTERDAY BOOK	
142: JOHN BUY *FUTURE WHAT *WHAT	JOHN BUY
YESTERDAY WHAT BOOK	
158: LOVE JOHN *JOHN	LOVE JOH
N WHO	
167: JOHN IX *IX *WHAT MARY	JOHN IX
SAY LOVE MARY	JOHN IX
	JOHN MAD
171: JOHN *JOHN BLAME	JOHN MAR
Y BLAME	
174: *GIVE1 *LOVE GIVE1 *JOHN *CAR	PEOPLE G
ROUP GIVE1 JANA TOY	
181: JOHN ARRIVE	JOHN ARR
IVE	
184: *IX *JOHN *GIVE1 TEACHER *MARY	ALL BOY
GIVE TEACHER APPLE	
189: JOHN *JOHN *ARRIVE	JOHN GIV
E GIRL BOX	
193: JOHN *IX *WOMAN BOX	JOHN GIV
E GIRL BOX	331
199: *JOHN *WHAT *MARY	LIKE CHO
	LIKE CHO
COLATE WHO	70UN TEI
201: JOHN *IX *IX *JOHN BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	
running: ['delta-rx', 'delta-ry', 'delta-lx', 'delta-ly'] <class< td=""><td>my_mode</td></class<>	my_mode
<pre>l_selectors.SelectorCV'&gt;</pre>	
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\*\*\*\* WER = 0.6629213483146067 Total correct: 60 out of 178

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2: JOHN *IX HOMEWORK	JOHN WRI
TE HOMEWORK	701111 6441
7: JOHN *TOY *HOMEWORK *TOY	JOHN CAN
GO CAN 12: JOHN *BOX *GROUP CAN	JOHN CAN
GO CAN	JUNN CAN
21: JOHN *VISIT *CHICAGO *MARY *GO2 *HOMEWORK *TOMORROW *MARY	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	JOHN F13
25: JOHN *IX IX IX	JOHN LIK
E IX IX IX	JOIN LIK
28: JOHN *IX IX IX IX	JOHN LIK
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30: JOHN *IX *WHO *JOHN IX	JOHN LIK
E IX IX IX	
36: *IX *IX *IX IX *MARY *IX	MARY VEG
ETABLE KNOW IX LIKE CORN1	
40: *MARY IX *JOHN *IX *IX	JOHN IX
THINK MARY LOVE	
43: JOHN *IX *GO HOUSE	JOHN MUS
T BUY HOUSE	
50: *JOHN *WHO BUY CAR *JOHN	FUTURE J
OHN BUY CAR SHOULD	
54: JOHN *JOHN *IX BUY *BOOK	JOHN SHO
ULD NOT BUY HOUSE	
57: *WHO *JOHN *IX *IX	JOHN DEC
IDE VISIT MARY	JOHN FUT
67: JOHN *WHO *LOVE *NEXT-WEEK *LOVE	JOHN FUT
URE NOT BUY HOUSE	JOHN WIL
71: JOHN *VISIT VISIT *BOOK L VISIT MARY	JOHN MIL
74: JOHN *WHO *IX MARY	JOHN NOT
VISIT MARY	JOHN NOT
77: *JOHN *GIVE1 *IX	ANN BLAM
E MARY	7.1.11.
84: *JOHN *BORROW *IX BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	
89: *WOMAN IX *IX *IX IX *TOY	JOHN IX
GIVE MAN IX NEW COAT	
90: *IX *IX *JOHN *IX *IX *IX	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
92: JOHN *IX IX *IX *POSS *GROUP	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
100: *JOHN NEW CAR *HOMEWORK	POSS NEW
CAR BREAK-DOWN	
105: JOHN *IX	JOHN LEG
107: JOHN *JOHN *TOY *PUTASIDE *MARY	JOHN POS
S FRIEND HAVE CANDY	LIOMANI AD
108: *JOHN *POTATO	WOMAN AR
RIVE 113: *JOHN CAR *MARY *MARY *GIVE1	IX CAR B
LUE SUE BUY	IV CAK B
119: *JOHN *GIVE1 *WHAT CAR *WHAT	SUE BUY
IX CAR BLUE	JUL DU1
122: JOHN *CAR BOOK	JOHN REA
D BOOK	··-·

139: JOHN BUY WHAT *IX *ARRIVE WHAT YESTERDAY BOOK	JOHN BUY
142: JOHN BUY *IX WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK 158: *BORROW *WHAT *JOHN	LOVE JOH
N WHO	LOVE JOH
167: JOHN IX *IX *ARRIVE *WHAT SAY LOVE MARY	JOHN IX
171: *IX *JOHN *BORROW	JOHN MAR
Y BLAME	PEOPLE G
174: *BORROW *IX GIVE1 *IX TOY ROUP GIVE1 JANA TOY	PEUPLE G
181: JOHN ARRIVE	JOHN ARR
IVE 184: *IX *JOHN *GIVE1 *TOY *WHAT	ALL BOY
GIVE TEACHER APPLE	
189: JOHN *IX *JOHN *WHAT E GIRL BOX	JOHN GIV
193: JOHN *IX *IX BOX	JOHN GIV
E GIRL BOX 199: *JOHN *WHAT *MARY	LIKE CHO
COLATE WHO	LIKE CHO
201: JOHN *IX *IX *POSS *BORROW HOUSE L MARY IX-1P BUY HOUSE	JOHN TEL
running: ['dist-norm-left-right', 'delta-dist-norm-left-right']	<class 'm<="" td=""></class>
<pre>y_model_selectors.SelectorConstant'&gt;</pre>	
**** WER = 0.8651685393258427	
Total correct: 24 out of 178	
Video Recognized	Correct
Video Recognized	
Video Recognized	
Video Recognized ====================================	JOHN WRI
Video Recognized ====================================	=======
Video Recognized  ===================================	JOHN WRI
Video Recognized ====================================	JOHN WRI
Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS
Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN
Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS
Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK
Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK  JOHN LIK
Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK
Video Recognized	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK  JOHN LIK
Video Recognized	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK  MARY VEG  JOHN IX
Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK  JOHN LIK  MARY VEG  JOHN IX  JOHN MUS
Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK  MARY VEG  JOHN IX
Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK  JOHN LIK  MARY VEG  JOHN IX  JOHN MUS
Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK  JOHN LIK  MARY VEG  JOHN IX  JOHN MUS  FUTURE J

IDE VISIT MARY	
67: *WONT FUTURE NOT BUY *CAN	JOHN FUT
URE NOT BUY HOUSE	70.00
71: *BUY WILL *JOHN *VISIT L VISIT MARY	JOHN WIL
74: *TOY1 *CANDY *NOT *PREFER	JOHN NOT
VISIT MARY	5
77: ANN *STUDENT *BUT F MARY	ANN BLAM
84: *BROTHER *BUY1 *ARRIVE *SAY	IX-1P FI
ND SOMETHING-ONE BOOK	
89: *YESTERDAY *PUTASIDE *GO1 *SOMETHING-ONE *HOUSE *SHOOT *BOOK GIVE MAN IX NEW COAT	JOHN IX
90: *VEGETABLE *FUTURE *GO1 *ALL *HAVE BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
92: *SHOOT *YESTERDAY *WHAT *TEACHER *TEACHER *NEXT-WEEK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK  100: *LOVE NEW *STOLEN BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	1033 NEW
105: *SEE *GIRL	JOHN LEG
107: *LIKE *NEW *ARRIVE *WONT *SAY-1P S FRIEND HAVE CANDY	JOHN POS
108: *NEXT-WEEK *SOMETHING-ONE	WOMAN AR
RIVE	
113: *SHOOT *BOX *VEGETABLE *NOT *BUY1	IX CAR B
LUE SUE BUY 119: *JANA *BUY1 *LOVE *HOMEWORK *FRIEND	SUE BUY
IX CAR BLUE	302 201
122: *BUY *ARRIVE *APPLE	JOHN REA
D BOOK 139: *WONT *BUY1 *LOVE *GO1 BOOK	JOHN BUY
WHAT YESTERDAY BOOK	JOHN DOT
142: *BREAK-DOWN *FRIEND *CHICAGO WHAT *CORN	JOHN BUY
YESTERDAY WHAT BOOK	10//5 70//
158: *BLAME *BOY *PREFER N WHO	LOVE JOH
167: *WONT *BUY *SAY-1P LOVE *BOY	JOHN IX
SAY LOVE MARY	
171: *LIKE *MOTHER BLAME Y BLAME	JOHN MAR
174: *ARRIVE *YESTERDAY *CAR *CORN1 *LOVE	PEOPLE G
ROUP GIVE1 JANA TOY	
181: *TEACHER ARRIVE IVE	JOHN ARR
184: *GIVE1 *FRIEND *GIVE1 TEACHER *PREFER	ALL BOY
GIVE TEACHER APPLE	
189: *WHO *VEGETABLE *PREFER BOX	JOHN GIV
E GIRL BOX 193: *SUE *HERE GIRL *CAR	JOHN GIV
E GIRL BOX	301114 014
199: *OLD *WONT *SEE	LIKE CHO
COLATE WHO 201: JOHN *THINK *COAT *NOT BUY *GIVE	JOHN TEL
L MARY IX-1P BUY HOUSE	JOHN IEL
running: ['dist-norm-left-right', 'delta-dist-norm-left-right']	<class 'm<="" td=""></class>
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\*\*\*\* WER = 0.9213483146067416 Total correct: 14 out of 178

Total correct: 14 out of 178	
Video Recognized	Correct
	=======
=======================================	
2: *CHOCOLATE *STUDENT *JOHN	JOHN WRI
TE HOMEWORK	701N CAN
7: *SEE *ARRIVE *IX CAN	JOHN CAN
GO CAN 12: *LOVE *ALL *IX *HOUSE	JOHN CAN
GO CAN	JOHN CAN
21: *MARY *BILL *SHOULD *SUE *CAR *BLAME *SUE *WHO	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	301111 1 13
25: *MANY *GIVE2 *HOUSE *MAN *CAN	JOHN LIK
E IX IX IX	
28: *ANN *GIVE3 *PEOPLE *NEW *LOVE	JOHN LIK
E IX IX IX	
30: *SHOULD *MOTHER *KNOW *SHOULD *NAME	JOHN LIK
E IX IX IX	
36: *SUE *SAY *YESTERDAY *FRANK *COAT *CHOCOLATE	MARY VEG
ETABLE KNOW IX LIKE CORN1	
40: *TOY1 *POSS *WHO *SAY-1P *WHO	JOHN IX
THINK MARY LOVE	
43: *GO *PREFER *FRIEND HOUSE	JOHN MUS
T BUY HOUSE	FUTURE 7
50: *KNOW *BREAK-DOWN *ARRIVE CAR *PEOPLE OHN BUY CAR SHOULD	FUTURE J
54: *TOY1 *PREFER *SHOULD *STUDENT *GO	JOHN SHO
ULD NOT BUY HOUSE	JOHN JHO
57: *SHOULD *SELF *POSS *BREAK-DOWN	JOHN DEC
IDE VISIT MARY	55 525
67: *BUY1 FUTURE NOT *SHOOT *CAN	JOHN FUT
URE NOT BUY HOUSE	
71: *LOVE *SHOULD *ARRIVE *FUTURE	JOHN WIL
L VISIT MARY	
74: *HOMEWORK *LEAVE *SHOULD *WRITE	JOHN NOT
VISIT MARY	
77: *SOMETHING-ONE *LOVE *HAVE	ANN BLAM
E MARY	
84: *BROTHER *BLAME *WRITE *PAST	IX-1P FI
ND SOMETHING-ONE BOOK 89: *YESTERDAY *YESTERDAY *GO *BREAK-DOWN *HOUSE *POSS *FRANK	JOHN IX
GIVE MAN IX NEW COAT	JOHN IX
90: *VEGETABLE *POSS *STOLEN *TEACHER WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	JOINT GIV
92: *ARRIVE *POSS *WHAT *HOUSE *CAN *GO	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
100: *LOVE NEW CAR *WOMAN	POSS NEW
CAR BREAK-DOWN	
105: *YESTERDAY *SEE	JOHN LEG
107: *CHOCOLATE *LOVE *ARRIVE *BUY1 *SUE	JOHN POS
S FRIEND HAVE CANDY	
108: *SOMETHING-ONE *HOMEWORK	WOMAN AR
RIVE	<b>T</b> V <b>2</b>
113: *ARRIVE *POSS *LIKE *MAN *LOVE	IX CAR B
LUE SUE BUY	CHE DIN
119: *JANA *ARRIVE *CAR *POSS *SHOULD	SUE BUY

IX CAR BLUE	
122: *ARRIVE *ARRIVE *COAT	JOHN REA
D BOOK 139: *TOMORROW *ARRIVE *LOVE *IX *DECIDE	JOHN BUY
WHAT YESTERDAY BOOK 142: *BREAK-DOWN *SOMETHING-ONE *CAR WHAT *FRANK	JOHN BUY
YESTERDAY WHAT BOOK	JOHN BUT
158: *CAR *MARY *CORN1 N WHO	LOVE JOH
167: *CHOCOLATE *YESTERDAY *SAY-1P *GO *CAR	JOHN IX
SAY LOVE MARY 171: *OLD *SUE BLAME	JOHN MAR
Y BLAME 174: *CAN *COAT *CAR *WHO *LOVE	PEOPLE G
ROUP GIVE1 JANA TOY	PEOPLE G
181: *HOUSE ARRIVE	JOHN ARR
IVE	
184: *GIVE1 *WHO *GIVE1 *CAN *WRITE	ALL BOY
GIVE TEACHER APPLE	JOHN CTV
189: *SUE *GO *CORN BOX E GIRL BOX	JOHN GIV
193: *SAY *YESTERDAY *PAST *CAR	JOHN GIV
E GIRL BOX 199: *CHICKEN *OLD *SEE	LIKE CHO
COLATE WHO	LIKE CHO
201: *BUY *VEGETABLE *YESTERDAY *LIKE BUY *GIVE L MARY IX-1P BUY HOUSE	JOHN TEL
running: ['dist-norm-left-right', 'delta-dist-norm-left-right']	<class 'm<="" td=""></class>
<pre>y_model_selectors.SelectorDIC'&gt;</pre>	
y_model_selectors.selectorbic >	
**** WER = 0.8370786516853933	
**** WER = 0.8370786516853933 Total correct: 29 out of 178	Connect
**** WER = 0.8370786516853933 Total correct: 29 out of 178 Video Recognized	Correct
**** WER = 0.8370786516853933 Total correct: 29 out of 178	
**** WER = 0.8370786516853933  Total correct: 29 out of 178  Video Recognized ====================================	
**** WER = 0.8370786516853933  Total correct: 29 out of 178  Video Recognized ====================================	=======
**** WER = 0.8370786516853933  Total correct: 29 out of 178  Video Recognized  ===================================	=======
**** WER = 0.8370786516853933  Total correct: 29 out of 178  Video Recognized ====================================	JOHN WRI
**** WER = 0.8370786516853933  Total correct: 29 out of 178  Video Recognized  ===================================	JOHN WRI
**** WER = 0.8370786516853933  Total correct: 29 out of 178  Video Recognized  ===================================	JOHN WRI
**** WER = 0.8370786516853933  Total correct: 29 out of 178  Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN
**** WER = 0.8370786516853933  Total correct: 29 out of 178  Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS
**** WER = 0.8370786516853933  Total correct: 29 out of 178  Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK
**** WER = 0.8370786516853933  Total correct: 29 out of 178  Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK
**** WER = 0.8370786516853933  Total correct: 29 out of 178  Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK
**** WER = 0.8370786516853933  Total correct: 29 out of 178  Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK  JOHN LIK
**** WER = 0.8370786516853933 Total correct: 29 out of 178 Video Recognized	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK  JOHN LIK  MARY VEG  JOHN IX
**** WER = 0.8370786516853933 Total correct: 29 out of 178 Video Recognized	JOHN WRI JOHN CAN JOHN CAN JOHN FIS JOHN LIK JOHN LIK JOHN LIK MARY VEG
**** WER = 0.8370786516853933 Total correct: 29 out of 178 Video Recognized	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK  JOHN LIK  MARY VEG  JOHN IX

54: *CHOCOLATE *KNOW *SHOULD *STUDENT *GO	JOHN SHO
ULD NOT BUY HOUSE  57: JOHN *LEAVE *IX *BREAK-DOWN  IDE VISIT MARY	JOHN DEC
67: JOHN FUTURE *GIRL *SHOOT *CAN URE NOT BUY HOUSE	JOHN FUT
71: *LOVE *SHOULD *ARRIVE *FUTURE L VISIT MARY	JOHN WIL
74: *TOY1 *CANDY *SHOULD *WRITE VISIT MARY	JOHN NOT
77: *SOMETHING-ONE *LOVE MARY E MARY	ANN BLAM
84: *BROTHER *IX *WRITE *PAST ND SOMETHING-ONE BOOK	IX-1P FI
89: *YESTERDAY *YESTERDAY *PEOPLE *BREAK-DOWN *HOUSE *POSS *APPLE GIVE MAN IX NEW COAT	JOHN IX
90: *VEGETABLE *POSS *LOVE *TEACHER WOMAN BOOK E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
92: JOHN *POSS IX *HOUSE *CAN BOOK E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
100: *IX NEW CAR *WOMAN CAR BREAK-DOWN	POSS NEW
105: *YESTERDAY *APPLE 107: JOHN *IX *ARRIVE *JOHN *SUE	JOHN LEG JOHN POS
S FRIEND HAVE CANDY  108: *SOMETHING-ONE *HOMEWORK	WOMAN AR
RIVE 113: *JOHN *POSS *MARY *MAN *BUY1	IX CAR B
LUE SUE BUY 119: *JANA *ARRIVE *CAR *POSS *BOX IX CAR BLUE	SUE BUY
122: JOHN *ARRIVE *APPLE D BOOK	JOHN REA
139: *TOMORROW *ARRIVE *LOVE *GIVE1 *DECIDE WHAT YESTERDAY BOOK	JOHN BUY
142: *WOMAN *LOVE *CAR WHAT *CORN YESTERDAY WHAT BOOK	JOHN BUY
158: *BLAME JOHN WHO N WHO	LOVE JOH
167: *CHOCOLATE *JOHN *SAY-1P *GO *JOHN SAY LOVE MARY	JOHN IX
171: *MARY *MOTHER *WHAT Y BLAME	JOHN MAR
174: *CAN *KNOW *BLAME *WHO *LOVE ROUP GIVE1 JANA TOY	PEOPLE G
181: *HOUSE ARRIVE IVE	JOHN ARR
184: *GIVE1 *WHO *GIVE1 *BROTHER *WRITE GIVE TEACHER APPLE	ALL BOY
189: *SUE *GO *NOT BOX E GIRL BOX	JOHN GIV
193: JOHN *KNOW *PAST *CAR E GIRL BOX	JOHN GIV
199: *CHICKEN CHOCOLATE *SEE COLATE WHO	LIKE CHO
201: JOHN *THINK *YESTERDAY *LIKE BUY *GIVE L MARY IX-1P BUY HOUSE	JOHN TEL

----running: ['dist-norm-left-right', 'delta-dist-norm-left-right'] <class 'm y model selectors.SelectorCV'>

y\_model\_selectors.SelectorCV'> \*\*\*\* WER = 0.8370786516853933 Total correct: 29 out of 178 Video Recognized Correct \_\_\_\_\_\_ 2: JOHN \*STUDENT \*MARY JOHN WRI TE HOMEWORK 7: JOHN \*LOVE \*MARY CAN JOHN CAN GO CAN 12: JOHN \*GO1 \*WHAT \*HOUSE JOHN CAN GO CAN 21: \*MARY \*BOY \*SUE \*JANA \*BLAME \*WHAT \*SUE \*JOHN JOHN FIS H WONT EAT BUT CAN EAT CHICKEN 25: \*BOX \*NEXT-WEEK \*HOUSE \*MAN IX JOHN LIK E IX IX IX 28: \*BOX \*MAN \*HOUSE \*BOX IX JOHN LIK E IX IX IX 30: \*WHO \*MOTHER \*PAST \*SHOULD \*LOVE JOHN LIK E IX IX IX 36: \*JOHN \*JOHN \*SHOULD \*BREAK-DOWN \*COAT \*JOHN MARY VEG ETABLE KNOW IX LIKE CORN1 40: \*TOY1 \*POSS \*FRANK \*EAT \*MARY JOHN IX THINK MARY LOVE 43: \*ARRIVE \*PREFER BUY HOUSE JOHN MUS T BUY HOUSE 50: \*SEE \*BREAK-DOWN \*LOVE CAR \*ARRIVE FUTURE J OHN BUY CAR SHOULD 54: \*LAST-WEEK \*FUTURE1 \*WHO \*HAVE \*IX JOHN SHO ULD NOT BUY HOUSE 57: \*SAY-1P \*FUTURE1 \*IX \*BREAK-DOWN JOHN DEC IDE VISIT MARY 67: \*WOMAN \*IX \*GIRL \*ARRIVE \*CAN JOHN FUT URE NOT BUY HOUSE 71: \*BUY \*SHOULD \*JOHN \*JOHN JOHN WIL L VISIT MARY 74: JOHN \*CANDY \*LEAVE \*FIND JOHN NOT VISIT MARY 77: \*ARRIVE \*WHAT \*GO1 ANN BLAM E MARY 84: \*BROTHER \*SHOOT SOMETHING-ONE \*SOMETHING-ONE IX-1P FI ND SOMETHING-ONE BOOK 89: \*BOOK \*YESTERDAY \*CAN \*SOMETHING-ONE \*HOUSE NEW \*BOOK JOHN IX GIVE MAN IX NEW COAT 90: \*VEGETABLE \*FUTURE \*CAN \*BOX WOMAN \*IX JOHN GIV E IX SOMETHING-ONE WOMAN BOOK JOHN GIV 92: JOHN \*YESTERDAY IX \*HOUSE \*CAN BOOK E IX SOMETHING-ONE WOMAN BOOK POSS NEW 100: \*LOVE NEW \*WHAT \*WOMAN CAR BREAK-DOWN 105: \*YESTERDAY \*SOMETHING-ONE JOHN LEG 107: JOHN \*IX \*LOVE \*SHOULD \*MARY JOHN POS S FRIEND HAVE CANDY

WOMAN AR

108: \*SOMETHING-ONE \*JOHN

RIVE

113: *JOHN *TOY *COAT *YESTERDAY *BUY1	IX CAR B
LUE SUE BUY 119: *JANA *BUY1 *LOVE *FUTURE *SOMETHING-ONE IX CAR BLUE	SUE BUY
122: JOHN *LOVE *POSS D BOOK	JOHN REA
139: *BOY *LOVE *CAR *CAR *DECIDE WHAT YESTERDAY BOOK	JOHN BUY
142: *MARY *LOVE *NEW WHAT *BREAK-DOWN YESTERDAY WHAT BOOK	JOHN BUY
158: *BLAME *IX *NOT N WHO	LOVE JOH
167: *SHOULD *JOHN *COAT *CAN MARY SAY LOVE MARY	JOHN IX
171: *MARY *JOHN BLAME Y BLAME	JOHN MAR
174: *CAN *WOMAN *CAR *NOT *GIVE1 ROUP GIVE1 JANA TOY	PEOPLE G
181: *HOUSE *LOVE	JOHN ARR
184: *WHAT BOY *GIVE1 *CAN *PREFER GIVE TEACHER APPLE	ALL BOY
189: JOHN *MARY *PREFER BOX E GIRL BOX	JOHN GIV
193: JOHN *NEW *NOT *GIVE1 E GIRL BOX	JOHN GIV
199: *SHOULD *SHOULD *YESTERDAY COLATE WHO	LIKE CHO
201: JOHN *VEGETABLE *LEG *LIKE BUY HOUSE L MARY IX-1P BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'd ly'] <class 'my_model_selectors.selectorconstant'="">  **** WER = 0.5449438202247191</class>	
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'd ly'] <class 'my_model_selectors.selectorconstant'="">  **** WER = 0.5449438202247191 Total correct: 81 out of 178 Video Recognized</class>	elta-norm- Correct
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'd ly'] <class 'my_model_selectors.selectorconstant'="">  **** WER = 0.5449438202247191 Total correct: 81 out of 178</class>	elta-norm- Correct
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'd ly'] <class 'my_model_selectors.selectorconstant'="">  **** WER = 0.5449438202247191  Total correct: 81 out of 178  Video Recognized</class>	elta-norm- Correct
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'd ly'] <class 'my_model_selectors.selectorconstant'="">  **** WER = 0.5449438202247191 Total correct: 81 out of 178 Video Recognized</class>	elta-norm- Correct =======
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'd ly'] <class 'my_model_selectors.selectorconstant'="">  **** WER = 0.5449438202247191 Total correct: 81 out of 178 Video Recognized ====================================</class>	Correct
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'd ly'] <class 'my_model_selectors.selectorconstant'="">  **** WER = 0.5449438202247191  Total correct: 81 out of 178  Video Recognized</class>	Correct ======  JOHN WRI  JOHN CAN
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'd ly'] <class 'my_model_selectors.selectorconstant'="">  **** WER = 0.5449438202247191  Total correct: 81 out of 178  Video Recognized</class>	Correct ======  JOHN WRI  JOHN CAN  JOHN CAN
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'd ly'] <class 'my_model_selectors.selectorconstant'="">  **** WER = 0.5449438202247191  Total correct: 81 out of 178 Video Recognized ====================================</class>	Correct ======  JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'd ly'] <class 'my_model_selectors.selectorconstant'="">  **** WER = 0.5449438202247191 Total correct: 81 out of 178 Video Recognized </class>	Correct ======  JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'delty'] <class 'my_model_selectors.selectorconstant'="">  **** WER = 0.5449438202247191  Total correct: 81 out of 178  Video Recognized</class>	Correct ======  JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'd ly'] <class 'my_model_selectors.selectorconstant'="">  **** WER = 0.5449438202247191 Total correct: 81 out of 178 Video Recognized</class>	Correct ======  JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK  JOHN LIK
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'd' ly'] <class 'my_model_selectors.selectorconstant'="">  **** WER = 0.5449438202247191  Total correct: 81 out of 178  Video Recognized</class>	Correct ======  JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK  JOHN LIK  MARY VEG

T BUY HOUSE 50: *JOHN *WHO BUY CAR *MARY	FUTURE 3
OHN BUY CAR SHOULD	FUTURE J
54: JOHN *JOHN *WHO BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	
57: JOHN *JOHN *IX *JOHN	JOHN DEC
IDE VISIT MARY	
67: JOHN *JOHN BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	701111 1171
71: JOHN *JOHN VISIT MARY L VISIT MARY	JOHN WIL
74: JOHN *MARY *IX *JOHN	JOHN NOT
VISIT MARY	30
77: *JOHN BLAME *JOHN	ANN BLAM
E MARY	
84: *JOHN *NEW *IX *NEW	IX-1P FI
ND SOMETHING-ONE BOOK	
89: JOHN *JOHN *IX *JOHN IX NEW *HOUSE	JOHN IX
GIVE MAN IX NEW COAT 90: *WHO *JOHN *JOHN *IX *IX BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
92: JOHN *IX IX *JOHN WOMAN *ARRIVE	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
100: *JOHN NEW CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	
105: JOHN *JOHN	JOHN LEG
107: JOHN *IX FRIEND HAVE *JOHN	JOHN POS
S FRIEND HAVE CANDY	
100. *TOUN ADDIVE	LIOMANI AD
108: *JOHN ARRIVE	WOMAN AR
108: *JOHN ARRIVE RIVE 113: *JOHN CAR *MARY *MARY *BUY1	WOMAN AR  IX CAR B
RIVE	
RIVE 113: *JOHN CAR *MARY *MARY *BUY1	
RIVE 113: *JOHN CAR *MARY *MARY *BUY1 LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY IX CAR BLUE	IX CAR B SUE BUY
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RIVE 113: *JOHN CAR *MARY *MARY *BUY1 LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY IX CAR BLUE 122: JOHN READ *YESTERDAY D BOOK	IX CAR B SUE BUY JOHN REA
RIVE 113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY  IX CAR BLUE 122: JOHN READ *YESTERDAY  D BOOK 139: JOHN *BUY1 WHAT *JOHN *STOLEN	IX CAR B SUE BUY
RIVE 113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY  IX CAR BLUE 122: JOHN READ *YESTERDAY  D BOOK 139: JOHN *BUY1 WHAT *JOHN *STOLEN WHAT YESTERDAY BOOK	IX CAR B SUE BUY JOHN REA JOHN BUY
RIVE 113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY  IX CAR BLUE 122: JOHN READ *YESTERDAY  D BOOK 139: JOHN *BUY1 WHAT *JOHN *STOLEN  WHAT YESTERDAY BOOK 142: JOHN BUY YESTERDAY WHAT *YESTERDAY	IX CAR B SUE BUY JOHN REA
RIVE 113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY  IX CAR BLUE 122: JOHN READ *YESTERDAY  D BOOK 139: JOHN *BUY1 WHAT *JOHN *STOLEN WHAT YESTERDAY BOOK	IX CAR B SUE BUY JOHN REA JOHN BUY
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RIVE  113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY  119: *JOHN *BUY1 IX CAR *MARY  IX CAR BLUE  122: JOHN READ *YESTERDAY  D BOOK  139: JOHN *BUY1 WHAT *JOHN *STOLEN  WHAT YESTERDAY BOOK  142: JOHN BUY YESTERDAY WHAT *YESTERDAY  YESTERDAY WHAT BOOK  158: LOVE *IX WHO  N WHO  167: JOHN IX *LIKE LOVE *HERE  SAY LOVE MARY	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX
RIVE  113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY  119: *JOHN *BUY1 IX CAR *MARY  IX CAR BLUE  122: JOHN READ *YESTERDAY  D BOOK  139: JOHN *BUY1 WHAT *JOHN *STOLEN  WHAT YESTERDAY BOOK  142: JOHN BUY YESTERDAY WHAT *YESTERDAY  YESTERDAY WHAT BOOK  158: LOVE *IX WHO  N WHO  167: JOHN IX *LIKE LOVE *HERE  SAY LOVE MARY  171: JOHN *JOHN BLAME	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH
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RIVE  113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY  119: *JOHN *BUY1 IX CAR *MARY  IX CAR BLUE  122: JOHN READ *YESTERDAY  D BOOK  139: JOHN *BUY1 WHAT *JOHN *STOLEN  WHAT YESTERDAY BOOK  142: JOHN BUY YESTERDAY WHAT *YESTERDAY  YESTERDAY WHAT BOOK  158: LOVE *IX WHO  N WHO  167: JOHN IX *LIKE LOVE *HERE  SAY LOVE MARY  171: JOHN *JOHN BLAME  Y BLAME  174: *CAR *LOVE GIVE1 *WHAT *FINISH  ROUP GIVE1 JANA TOY  181: JOHN *GIVE1  IVE  184: *IX *WHO *GIVE1 TEACHER *MARY  GIVE TEACHER APPLE  189: JOHN *IX *WHAT *WHAT	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX JOHN MAR PEOPLE G JOHN ARR
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RIVE  113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY  119: *JOHN *BUY1 IX CAR *MARY  IX CAR BLUE  122: JOHN READ *YESTERDAY  D BOOK  139: JOHN *BUY1 WHAT *JOHN *STOLEN  WHAT YESTERDAY BOOK  142: JOHN BUY YESTERDAY WHAT *YESTERDAY  YESTERDAY WHAT BOOK  158: LOVE *IX WHO  N WHO  167: JOHN IX *LIKE LOVE *HERE  SAY LOVE MARY  171: JOHN *JOHN BLAME  Y BLAME  174: *CAR *LOVE GIVE1 *WHAT *FINISH  ROUP GIVE1 JANA TOY  181: JOHN *GIVE1  IVE  184: *IX *WHO *GIVE1 TEACHER *MARY  GIVE TEACHER APPLE  189: JOHN *IX *WHAT *WHAT  E GIRL BOX  193: JOHN *IX *IX BOX	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX JOHN MAR PEOPLE G JOHN ARR ALL BOY
RIVE  113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY  119: *JOHN *BUY1 IX CAR *MARY  IX CAR BLUE  122: JOHN READ *YESTERDAY  D BOOK  139: JOHN *BUY1 WHAT *JOHN *STOLEN  WHAT YESTERDAY BOOK  142: JOHN BUY YESTERDAY WHAT *YESTERDAY  YESTERDAY WHAT BOOK  158: LOVE *IX WHO  N WHO  167: JOHN IX *LIKE LOVE *HERE  SAY LOVE MARY  171: JOHN *JOHN BLAME  Y BLAME  174: *CAR *LOVE GIVE1 *WHAT *FINISH  ROUP GIVE1 JANA TOY  181: JOHN *GIVE1  IVE  184: *IX *WHO *GIVE1 TEACHER *MARY  GIVE TEACHER APPLE  189: JOHN *IX *WHAT *WHAT  E GIRL BOX	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX JOHN MAR PEOPLE G JOHN ARR ALL BOY JOHN GIV

201: JOHN \*IX MARY \*IX \*VISIT HOUSE JOHN TEL

L MARY IX-1P BUY HOUSE

----running: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'delta-normly'] <class 'my\_model\_selectors.SelectorBIC'>

\*\*\*\* WER = 0.6123595505617978

Total correct: 69 out of 178

100: \*JOHN NEW CAR BREAK-DOWN

107: JOHN \*IX \*VISIT \*VISIT \*MARY

CAR BREAK-DOWN 105: JOHN \*JOHN

Video Recognized	Correct
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2: JOHN *JOHN *SAY	JOHN WRI
TE HOMEWORK	JOHN CAN
7: JOHN *VISIT *CAR *TEACHER GO CAN	JOHN CAN
12: JOHN *BOX *GO1 CAN	JOHN CAN
GO CAN	JOHN CAN
21: JOHN FISH *KNOW *JANA *VISIT *VISIT *MARY *EAT	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	301111 1 13
25: JOHN *MARY *MARY IX IX	JOHN LIK
E IX IX IX	
28: JOHN *MARY IX IX IX	JOHN LIK
E IX IX IX	
30: JOHN *IX *MARY *JOHN IX	JOHN LIK
E IX IX IX	
36: MARY *MARY *JOHN IX *IX *JOHN	MARY VEG
ETABLE KNOW IX LIKE CORN1	
40: *SOMETHING-ONE IX *SHOULD MARY *MARY	JOHN IX
THINK MARY LOVE	
43: JOHN *JOHN *HOUSE HOUSE	JOHN MUS
T BUY HOUSE	FUTURE 3
50: *JOHN *IX BUY CAR *MARY	FUTURE J
OHN BUY CAR SHOULD	JOHN CHO
54: JOHN *JOHN *WHO BUY HOUSE ULD NOT BUY HOUSE	JOHN SHO
57: JOHN *MARY *IX *JOHN	JOHN DEC
IDE VISIT MARY	JOHN DEC
67: JOHN *JOHN *IX *NEW HOUSE	JOHN FUT
URE NOT BUY HOUSE	301
71: JOHN *IX *BOX MARY	JOHN WIL
L VISIT MARY	
74: JOHN *MARY *IX *JOHN	JOHN NOT
VISIT MARY	
77: *JOHN BLAME MARY	ANN BLAM
E MARY	
84: *JOHN *WHAT *IX BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	_
89: *SHOULD *JOHN *IX *JOHN IX *WHAT *CAN	JOHN IX
GIVE MAN IX NEW COAT	70.00
90: *WHO *JOHN *JOHN *IX *IX BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	JOHN CTV
92: JOHN *IX IX *JOHN *IX *VISIT E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
T TV DOLIFILING-ONE MOLINIA DOOK	

POSS NEW

JOHN LEG

JOHN POS

S FRIEND HAVE CANDY	
108: *JOHN ARRIVE	WOMAN AR
RIVE 113: *JOHN CAR *MARY *MARY *BUY1	IX CAR B
LUE SUE BUY	
119: *JOHN *BUY1 IX CAR *MARY IX CAR BLUE	SUE BUY
122: JOHN *VISIT BOOK	JOHN REA
D BOOK	701B1 B187
139: JOHN *GIVE1 *CAR *JOHN *CAR WHAT YESTERDAY BOOK	JOHN BUY
142: JOHN BUY *JOHN *MARY BOOK	JOHN BUY
YESTERDAY WHAT BOOK	
158: *ARRIVE *IX WHO N WHO	LOVE JOH
167: JOHN IX *IX *GIVE1 MARY	JOHN IX
SAY LOVE MARY	
171: JOHN *JOHN BLAME Y BLAME	JOHN MAR
174: *VISIT *MARY GIVE1 *MARY *CAR	PEOPLE G
ROUP GIVE1 JANA TOY	
181: *MARY ARRIVE IVE	JOHN ARR
184: *IX *WHO *GIVE1 TEACHER *MARY	ALL BOY
GIVE TEACHER APPLE	
189: JOHN *IX *WHO *ARRIVE E GIRL BOX	JOHN GIV
193: JOHN *IX *IX BOX	JOHN GIV
E GIRL BOX	
199: *JOHN *LOVE WHO COLATE WHO	LIKE CHO
201: JOHN *IX *LOVE *IX *VISIT HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	
running: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'd	delta-norm-
<pre>ly'] <class 'my_model_selectors.selectordic'=""></class></pre>	
**** WER = 0.5955056179775281	
Total correct: 72 out of 178	Correct
Video Recognized	
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2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK 7: JOHN *HAVE *CAR *VISIT	JOHN CAN
GO CAN	
12: JOHN *BOX *GO1 CAN	JOHN CAN
GO CAN 21: JOHN FISH *GIVE1 *MARY BUT *BLAME *MARY *MARY	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	
25: JOHN *WHAT *JOHN IX *CORN	JOHN LIK
E IX IX IX 28: JOHN *MARY *JOHN *JOHN IX	JOHN LIK
E IX IX IX	55 LIN
30: JOHN *MARY *PUTASIDE *JOHN IX	JOHN LIK
E IX IX 36: *JOHN *JOHN *JOHN *GIVE *JOHN *JOHN	MARY VEG
ETABLE KNOW IX LIKE CORN1	

40: JOHN IX *JOHN MARY *MARY	JOHN IX
THINK MARY LOVE 43: JOHN *WOMAN *GO HOUSE T BUY HOUSE	JOHN MUS
50: *JOHN *VISIT BUY CAR *MARY OHN BUY CAR SHOULD	FUTURE J
54: JOHN *JOHN *WHO BUY HOUSE ULD NOT BUY HOUSE	JOHN SHO
57: JOHN *JOHN *SOMETHING-ONE *JOHN IDE VISIT MARY	JOHN DEC
67: JOHN *JOHN *WOMAN *NEW HOUSE URE NOT BUY HOUSE	JOHN FUT
71: JOHN *JOHN VISIT *CAR L VISIT MARY	JOHN WIL
74: JOHN *JOHN *MARY MARY VISIT MARY	JOHN NOT
77: *JOHN BLAME *JOHN E MARY	ANN BLAM
84: *JOHN *CAR *JOHN BOOK ND SOMETHING-ONE BOOK	IX-1P FI
89: JOHN *JOHN GIVE *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT	JOHN IX
90: JOHN *JOHN *GIVE WOMAN BOOK E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
92: JOHN *IX *JOHN *JOHN WOMAN *JOHN E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
100: *JOHN NEW CAR *BOOK CAR BREAK-DOWN	POSS NEW
105: JOHN *JOHN	JOHN LEG
107: JOHN *JOHN FRIEND *JOHN *JOHN	JOHN POS
107: JOHN *JOHN FRIEND *JOHN *JOHN S FRIEND HAVE CANDY	JOHN POS
S FRIEND HAVE CANDY 108: *JOHN ARRIVE	JOHN POS WOMAN AR
S FRIEND HAVE CANDY 108: *JOHN ARRIVE RIVE	WOMAN AR
S FRIEND HAVE CANDY 108: *JOHN ARRIVE RIVE 113: *JOHN CAR *MARY *JOHN *BUY1	
S FRIEND HAVE CANDY 108: *JOHN ARRIVE RIVE	WOMAN AR
S FRIEND HAVE CANDY 108: *JOHN ARRIVE RIVE 113: *JOHN CAR *MARY *JOHN *BUY1 LUE SUE BUY	WOMAN AR
S FRIEND HAVE CANDY 108: *JOHN ARRIVE RIVE 113: *JOHN CAR *MARY *JOHN *BUY1 LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY	WOMAN AR
S FRIEND HAVE CANDY 108: *JOHN ARRIVE RIVE 113: *JOHN CAR *MARY *JOHN *BUY1 LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY IX CAR BLUE 122: JOHN *CAR BOOK D BOOK	WOMAN AR IX CAR B SUE BUY JOHN REA
S FRIEND HAVE CANDY 108: *JOHN ARRIVE RIVE 113: *JOHN CAR *MARY *JOHN *BUY1 LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY IX CAR BLUE 122: JOHN *CAR BOOK D BOOK 139: JOHN *BUY1 *CAR *JOHN *MARY	WOMAN AR  IX CAR B  SUE BUY
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S FRIEND HAVE CANDY  108: *JOHN ARRIVE  RIVE  113: *JOHN CAR *MARY *JOHN *BUY1  LUE SUE BUY  119: *JOHN *BUY1 IX CAR *MARY  IX CAR BLUE  122: JOHN *CAR BOOK  D BOOK  139: JOHN *BUY1 *CAR *JOHN *MARY  WHAT YESTERDAY BOOK  142: JOHN BUY *JOHN WHAT *CAR  YESTERDAY WHAT BOOK  158: *JOHN JOHN *JOHN  N WHO  167: JOHN IX *OLD *GIVE1 MARY	WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY
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S FRIEND HAVE CANDY  108: *JOHN ARRIVE  RIVE  113: *JOHN CAR *MARY *JOHN *BUY1  LUE SUE BUY  119: *JOHN *BUY1 IX CAR *MARY  IX CAR BLUE  122: JOHN *CAR BOOK  D BOOK  139: JOHN *BUY1 *CAR *JOHN *MARY  WHAT YESTERDAY BOOK  142: JOHN BUY *JOHN WHAT *CAR  YESTERDAY WHAT BOOK  158: *JOHN JOHN *JOHN  N WHO  167: JOHN IX *OLD *GIVE1 MARY  SAY LOVE MARY	WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX
S FRIEND HAVE CANDY 108: *JOHN ARRIVE RIVE 113: *JOHN CAR *MARY *JOHN *BUY1 LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY IX CAR BLUE 122: JOHN *CAR BOOK D BOOK 139: JOHN *BUY1 *CAR *JOHN *MARY WHAT YESTERDAY BOOK 142: JOHN BUY *JOHN WHAT *CAR YESTERDAY WHAT BOOK 158: *JOHN JOHN *JOHN N WHO 167: JOHN IX *OLD *GIVE1 MARY SAY LOVE MARY 171: JOHN *JOHN BLAME Y BLAME 174: *CAR *JOHN GIVE1 *JOHN *CAR	WOMAN AR  IX CAR B  SUE BUY  JOHN REA  JOHN BUY  LOVE JOH  JOHN IX  JOHN MAR
S FRIEND HAVE CANDY 108: *JOHN ARRIVE RIVE 113: *JOHN CAR *MARY *JOHN *BUY1 LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY IX CAR BLUE 122: JOHN *CAR BOOK D BOOK 139: JOHN *BUY1 *CAR *JOHN *MARY WHAT YESTERDAY BOOK 142: JOHN BUY *JOHN WHAT *CAR YESTERDAY WHAT BOOK 158: *JOHN JOHN *JOHN N WHO 167: JOHN IX *OLD *GIVE1 MARY SAY LOVE MARY 171: JOHN *JOHN BLAME Y BLAME 174: *CAR *JOHN GIVE1 *JOHN *CAR ROUP GIVE1 JANA TOY 181: JOHN ARRIVE	WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX JOHN MAR PEOPLE G

193: JOHN *JOHN *WOMAN BOX	JOHN GIV
E GIRL BOX	JOHN GIV
199: *JOHN *JOHN *MARY COLATE WHO	LIKE CHO
201: JOHN *MARY *JOHN *WOMAN BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	
running: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', '	delta-norm-
<pre>ly'] <class 'my_model_selectors.selectorcv'=""></class></pre>	
**** WER = 0.5955056179775281	
Total correct: 72 out of 178	
Video Recognized	Correct
2: JOHN *CAR HOMEWORK	JOHN WRI
TE HOMEWORK 7: JOHN *TOY *HOMEWORK *ARRIVE	JOHN CAN
GO CAN	JOHN CAN
12: JOHN *BOX *GO1 CAN	JOHN CAN
GO CAN	
21: JOHN *IX *TOMORROW *MARY *GO2 *HOMEWORK *FUTURE *MARY	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	70UN 1 TK
25: JOHN *VISIT IX IX IX E IX IX	JOHN LIK
28: JOHN *IX IX IX IX	JOHN LIK
E IX IX IX	
30: JOHN *IX *CANDY IX IX	JOHN LIK
E IX IX IX	
36: *JOHN *FUTURE *JOHN IX *IX *MARY ETABLE KNOW IX LIKE CORN1	MARY VEG
40: JOHN IX *JOHN MARY *MARY	JOHN IX
THINK MARY LOVE	JOHN IX
43: JOHN *ARRIVE *GO HOUSE	JOHN MUS
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50: *JOHN *VISIT BUY CAR *MARY	FUTURE J
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ULD NOT BUY HOUSE	JUHN 3HU
57: JOHN *VISIT *IX MARY	JOHN DEC
IDE VISIT MARY	
67: JOHN *JOHN *IX *NEXT-WEEK HOUSE	JOHN FUT
URE NOT BUY HOUSE	701111 1171
71: JOHN *JOHN VISIT *GROUP L VISIT MARY	JOHN WIL
74: JOHN *JOHN MARY	JOHN NOT
VISIT MARY	
77: *JOHN BLAME MARY	ANN BLAM
E MARY	
84: *ANN *CAR *WRITE BOOK	IX-1P FI
ND SOMETHING-ONE BOOK 89: JOHN *JOHN GIVE *IX *JOHN NEW *DECIDE	JOHN IX
GIVE MAN IX NEW COAT	3311117
90: *MARY *JOHN *JOHN *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
92: JOHN *IX *JOHN *JOHN WOMAN *BORROW	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN *BLAME CAR *HOMEWORK	POSS NEW
TOO. JOHN DEAME CAN HOMEWORK	NLW

CAR BREAK-DOWN	
105: JOHN *JOHN	JOHN LEG
107: JOHN *JOHN *TOY *PUTASIDE *JOHN	JOHN POS
S FRIEND HAVE CANDY	
108: *JOHN *HOMEWORK	WOMAN AR
RIVE	
113: *JOHN CAR *MARY *IX *BUY1	IX CAR B
LUE SUE BUY	
119: *JOHN *LOVE *WRITE CAR *FRIEND	SUE BUY
IX CAR BLUE 122: JOHN *PEOPLE BOOK	JOHN REA
D BOOK	JUHN KEA
139: JOHN BUY *CAR *JOHN *MARY	JOHN BUY
WHAT YESTERDAY BOOK	33
142: JOHN BUY *IX WHAT *LEG	JOHN BUY
YESTERDAY WHAT BOOK	
158: *BORROW *WHAT *JOHN	LOVE JOH
N WHO	
167: JOHN IX *LOVE LOVE *WHAT	JOHN IX
SAY LOVE MARY	JOHN MAD
171: JOHN *JOHN BLAME Y BLAME	JOHN MAR
174: *CAR *IX GIVE1 *WHAT *BLAME	PEOPLE G
ROUP GIVE1 JANA TOY	FLOFEL G
181: JOHN *TOY	JOHN ARR
IVE	
184: *GIVE *JOHN *CAR TEACHER *FUTURE	ALL BOY
GIVE TEACHER APPLE	
189: JOHN *JOHN *IX *ARRIVE	JOHN GIV
E GIRL BOX	
193: JOHN *JOHN *POSS BOX	JOHN GIV
E GIRL BOX 199: *JOHN *HAVE *MARY	LIKE CHO
COLATE WHO	LIKE CHO
201: JOHN *IX *WHO *WOMAN BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	30111 122
running: ['norm-polar-rr', 'norm-rtheta', 'norm-polar-lr', 'norm	ı-polar-lt
heta', 'delta-norm-polar-rr', 'delta-norm-rtheta', 'delta-norm-polar	·-lr', 'de
<pre>lta-norm-polar-ltheta'] <class 'my_model_selectors.selectorconstant'<="" pre=""></class></pre>	
**** WER = 0.4606741573033708	
Total correct: 96 out of 178	
Video Recognized	Correct
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2: *POSS WRITE HOMEWORK	JOHN WRI
TE HOMEWORK	
7: JOHN *HAVE GO *TOY	JOHN CAN
GO CAN	
12: JOHN *WHAT *GO1 *WHAT	JOHN CAN
GO CAN	
21: JOHN FISH WONT *WHO BUT *CAR *CHICKEN CHICKEN	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	70UN 171/
25: JOHN *TELL *LOVE *WHO IX E IX IX	JOHN LIK
28: JOHN *WHO *WHO IX	JOHN LIK
E IX IX IX	JOHN LIN

E IX IX IX  36: MARY WHO *GIRL *GIVE *MARY *MARY  TARRY WHO *GIRL *GIVE *MARY *MARY  40: JOHN *BILL *CORN MARY *MARY  THINK MARY LOVE  43: JOHN *POSS BUY HOUSE  50: *FRANK *SEE BUY CAR *ARRIVE  OHN BUY CAR SHOULD  54: JOHN SHOULD *FUTURE BUY HOUSE  JOHN SHO  ULD NOT BUY HOUSE  57: JOHN *PREFER VISIT MARY  67: JOHN FUTURE NOT BUY HOUSE  JOHN FUT  URE NOT BUY HOUSE  71: JOHN *FUTURE VISIT MARY  L VISIT MARY  74: JOHN *HOUSE VISIT MARY  JOHN WIL  VISIT MARY  74: JOHN *WHO *GIVE MARY  TOHN NOT  VISIT MARY  77: *JOHN BLAME MARY  BMARY  84: *LOVE *NEW *HOMEWORK BOOK  89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK  GIVE MAN IX NEW COAT  90: JOHN *GIVE IX *ALL WOMAN BOOK  1X-OHN GIV  E IX SOMETHING-ONE WOMAN BOOK  92: JOHN *WOMAN IX *WOMAN BOOK  JOHN GIV  E IX SOMETHING-ONE WOMAN BOOK
40: JOHN *BILL *CORN MARY *MARY THINK MARY LOVE 43: JOHN *POSS BUY HOUSE 50: *FRANK *SEE BUY CAR *ARRIVE  OHN BUY CAR SHOULD 54: JOHN SHOULD *FUTURE BUY HOUSE  JOHN SHO  ULD NOT BUY HOUSE 57: JOHN *PREFER VISIT MARY  67: JOHN FUTURE NOT BUY HOUSE  71: JOHN FUTURE NOT BUY HOUSE  71: JOHN *FUTURE VISIT MARY  67: JOHN *FUTURE VISIT MARY  74: JOHN *FUTURE VISIT MARY  74: JOHN *WHO *GIVE MARY  77: *JOHN BLAME MARY  84: *LOVE *NEW *HOMEWORK BOOK  89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK  6IVE MAN IX NEW COAT 90: JOHN *GIVE IX *ALL WOMAN BOOK  92: JOHN *WOMAN IX *WOMAN BOOK  JOHN GIV  E IX SOMETHING-ONE WOMAN BOOK  92: JOHN *WOMAN IX *WOMAN WOMAN BOOK  JOHN GIV
43: JOHN *POSS BUY HOUSE  50: *FRANK *SEE BUY CAR *ARRIVE  50: *FRANK *SEE BUY CAR *ARRIVE  50: *FRANK *SEE BUY CAR *ARRIVE  54: JOHN SHOULD  54: JOHN SHOULD *FUTURE BUY HOUSE  JOHN SHO  ULD NOT BUY HOUSE  57: JOHN *PREFER VISIT MARY  67: JOHN FUTURE NOT BUY HOUSE  URE NOT BUY HOUSE  71: JOHN *FUTURE NOT BUY HOUSE  VISIT MARY  74: JOHN *FUTURE VISIT MARY  10HN NOT  VISIT MARY  77: *JOHN BLAME MARY  84: *LOVE *NEW *HOMEWORK BOOK  89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK  GIVE MAN IX NEW COAT  90: JOHN *GIVE IX *ALL WOMAN BOOK  E IX SOMETHING-ONE WOMAN BOOK  92: JOHN *WOMAN IX *WOMAN WOMAN BOOK  JOHN GIV
T BUY HOUSE  50: *FRANK *SEE BUY CAR *ARRIVE  50HN BUY CAR SHOULD  54: JOHN SHOULD *FUTURE BUY HOUSE  JOHN SHO  ULD NOT BUY HOUSE  57: JOHN *PREFER VISIT MARY  67: JOHN FUTURE NOT BUY HOUSE  71: JOHN FUTURE NOT BUY HOUSE  71: JOHN *FUTURE VISIT MARY  L VISIT MARY  74: JOHN *WHO *GIVE MARY  77: *JOHN *WHO *GIVE MARY  **OHN NOT VISIT MARY  **OHN NOT VISIT MARY  **OHN BLAME MARY  **E MARY  84: *LOVE *NEW *HOMEWORK BOOK  **ROW **SEE*********************************
59: *FRANK *SEE BUY CAR *ARRIVE OHN BUY CAR SHOULD 54: JOHN SHOULD *FUTURE BUY HOUSE JOHN SHO ULD NOT BUY HOUSE 57: JOHN *PREFER VISIT MARY JOHN DEC  IDE VISIT MARY 67: JOHN FUTURE NOT BUY HOUSE URE NOT BUY HOUSE 71: JOHN *FUTURE VISIT MARY JOHN WIL  L VISIT MARY 74: JOHN *WHO *GIVE MARY VISIT MARY 77: *JOHN BLAME MARY ANN BLAM  E MARY 84: *LOVE *NEW *HOMEWORK BOOK 89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK GIVE MAN IX NEW COAT 90: JOHN *GIVE IX *ALL WOMAN BOOK 92: JOHN *WOMAN IX *WOMAN WOMAN BOOK JOHN GIV
54: JOHN SHOULD *FUTURE BUY HOUSE  ULD NOT BUY HOUSE  57: JOHN *PREFER VISIT MARY  67: JOHN FUTURE NOT BUY HOUSE  URE NOT BUY HOUSE  71: JOHN *FUTURE VISIT MARY  AVISIT MARY  74: JOHN *WHO *GIVE MARY  VISIT MARY  77: *JOHN BLAME MARY  ANN BLAME  E MARY  84: *LOVE *NEW *HOMEWORK BOOK  ND SOMETHING-ONE BOOK  89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK  GIVE MAN IX NEW COAT  90: JOHN *GIVE IX *ALL WOMAN BOOK  92: JOHN *WOMAN IX *WOMAN BOOK  JOHN GIV
ULD NOT BUY HOUSE  57: JOHN *PREFER VISIT MARY  67: JOHN FUTURE NOT BUY HOUSE  URE NOT BUY HOUSE  71: JOHN *FUTURE VISIT MARY  10: JOHN *FUTURE VISIT MARY  74: JOHN *WHO *GIVE MARY  74: JOHN *WHO *GIVE MARY  77: *JOHN BLAME MARY  84: *LOVE *NEW *HOMEWORK BOOK  ND SOMETHING-ONE BOOK  89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK  GIVE MAN IX NEW COAT  90: JOHN *GIVE1 IX *ALL WOMAN BOOK  92: JOHN *WOMAN IX *WOMAN WOMAN BOOK  JOHN GIV
57: JOHN *PREFER VISIT MARY  67: JOHN FUTURE NOT BUY HOUSE  71: JOHN *FUTURE VISIT MARY  71: JOHN *FUTURE VISIT MARY  74: JOHN *WHO *GIVE MARY  75: *JOHN BLAME MARY  77: *JOHN BLAME MARY  84: *LOVE *NEW *HOMEWORK BOOK  **ND SOMETHING-ONE BOOK  89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK  GIVE MAN IX NEW COAT  90: JOHN *GIVE1 IX *ALL WOMAN BOOK  82: JOHN *WOMAN IX *WOMAN BOOK  70: JOHN GIVE  BOOK  JOHN GIVE
67: JOHN FUTURE NOT BUY HOUSE  71: JOHN *FUTURE VISIT MARY  74: JOHN *WHO *GIVE MARY  77: *JOHN BLAME MARY  ANN BLAME  E MARY  84: *LOVE *NEW *HOMEWORK BOOK  ND SOMETHING-ONE BOOK  89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK  GIVE MAN IX NEW COAT  90: JOHN *GIVE1 IX *ALL WOMAN BOOK  92: JOHN *WOMAN IX *WOMAN WOMAN BOOK  JOHN GIVE  TOHN TOTOLOGY  JOHN GIVE
URE NOT BUY HOUSE 71: JOHN *FUTURE VISIT MARY  74: JOHN *WHO *GIVE MARY  74: JOHN *WHO *GIVE MARY  77: *JOHN BLAME MARY  ANN BLAME  E MARY  84: *LOVE *NEW *HOMEWORK BOOK  ND SOMETHING-ONE BOOK  89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK  GIVE MAN IX NEW COAT  90: JOHN *GIVE1 IX *ALL WOMAN BOOK  E IX SOMETHING-ONE WOMAN BOOK  92: JOHN *WOMAN IX *WOMAN WOMAN BOOK  JOHN GIV
71: JOHN *FUTURE VISIT MARY L VISIT MARY 74: JOHN *WHO *GIVE MARY VISIT MARY 77: *JOHN BLAME MARY ANN BLAM E MARY 84: *LOVE *NEW *HOMEWORK BOOK ND SOMETHING-ONE BOOK 89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK GIVE MAN IX NEW COAT 90: JOHN *GIVE1 IX *ALL WOMAN BOOK 92: JOHN *WOMAN IX *WOMAN WOMAN BOOK  92: JOHN *WOMAN IX *WOMAN WOMAN BOOK  JOHN GIV
L VISIT MARY 74: JOHN *WHO *GIVE MARY VISIT MARY 77: *JOHN BLAME MARY ANN BLAM E MARY 84: *LOVE *NEW *HOMEWORK BOOK ND SOMETHING-ONE BOOK 89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK GIVE MAN IX NEW COAT 90: JOHN *GIVE1 IX *ALL WOMAN BOOK 92: JOHN *WOMAN IX *WOMAN WOMAN BOOK  92: JOHN *WOMAN IX *WOMAN WOMAN BOOK  JOHN GIV
VISIT MARY 77: *JOHN BLAME MARY  E MARY 84: *LOVE *NEW *HOMEWORK BOOK  ND SOMETHING-ONE BOOK 89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK  GIVE MAN IX NEW COAT 90: JOHN *GIVE1 IX *ALL WOMAN BOOK  E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *WOMAN IX *WOMAN WOMAN BOOK  JOHN GIV
77: *JOHN BLAME MARY  E MARY  84: *LOVE *NEW *HOMEWORK BOOK  ND SOMETHING-ONE BOOK  89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK  GIVE MAN IX NEW COAT  90: JOHN *GIVE1 IX *ALL WOMAN BOOK  92: JOHN *WOMAN IX *WOMAN WOMAN BOOK  92: JOHN *WOMAN IX *WOMAN WOMAN BOOK  JOHN GIV
E MARY  84: *LOVE *NEW *HOMEWORK BOOK  ND SOMETHING-ONE BOOK  89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK  GIVE MAN IX NEW COAT  90: JOHN *GIVE1 IX *ALL WOMAN BOOK  E IX SOMETHING-ONE WOMAN BOOK  92: JOHN *WOMAN IX *WOMAN WOMAN BOOK  JOHN GIV
ND SOMETHING-ONE BOOK 89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK GIVE MAN IX NEW COAT 90: JOHN *GIVE1 IX *ALL WOMAN BOOK E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *WOMAN IX *WOMAN WOMAN BOOK JOHN GIV
89: *WILL IX *WOMAN *WILL *WILL NEW *BOOK GIVE MAN IX NEW COAT 90: JOHN *GIVE1 IX *ALL WOMAN BOOK E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *WOMAN IX *WOMAN WOMAN BOOK JOHN GIV
GIVE MAN IX NEW COAT 90: JOHN *GIVE1 IX *ALL WOMAN BOOK E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *WOMAN IX *WOMAN WOMAN BOOK JOHN GIV
90: JOHN *GIVE1 IX *ALL WOMAN BOOK E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *WOMAN IX *WOMAN WOMAN BOOK JOHN GIV
92: JOHN *WOMAN IX *WOMAN WOMAN BOOK JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK
100: POSS NEW CAR BREAK-DOWN POSS NEW
CAR BREAK-DOWN
105: JOHN *VEGETABLE JOHN LEG
107: JOHN POSS FRIEND *GO *WHO JOHN POS
S FRIEND HAVE CANDY  108: *THINK *BOOK WOMAN AR
RIVE
113: IX CAR BLUE *MARY *IX-1P IX CAR B
LUE SUE BUY
119: *PREFER *BUY1 *BLUE *TOY *SELF SUE BUY IX CAR BLUE
122: JOHN READ BOOK JOHN REA
D BOOK
139: *SHOULD *BUY1 WHAT YESTERDAY BOOK JOHN BUY WHAT YESTERDAY BOOK
142: JOHN BUY YESTERDAY WHAT BOOK JOHN BUY
YESTERDAY WHAT BOOK
158: LOVE *MARY WHO LOVE JOH
N WHO 167: JOHN *TOY1 *MARY *WOMAN MARY JOHN IX
SAY LOVE MARY
171: JOHN *JOHN BLAME JOHN MAR
Y BLAME
Y BLAME 174: PEOPLE GROUP GIVE1 *CORN TOY PEOPLE G

184: ALL BOY *GIVE1 TEACHER *CORN GIVE TEACHER APPLE	ALL BOY
189: JOHN *SELF *CORN *BUY1 E GIRL BOX	JOHN GIV
193: JOHN *SELF *GIVE1 BOX E GIRL BOX	JOHN GIV
199: *JOHN CHOCOLATE WHO COLATE WHO	LIKE CHO
201: JOHN *SHOULD *WOMAN *LOVE BUY HOUSE L MARY IX-1P BUY HOUSE	JOHN TEL
running: ['norm-polar-rr', 'norm-rtheta', 'norm-polar-lr', 'normheta', 'delta-norm-polar-rr', 'delta-norm-rtheta', 'delta-norm-polar-lta-norm-polar-ltheta'] <class 'my_model_selectors.selectorbic'=""></class>	
**** WER = 0.4606741573033708	
Total correct: 96 out of 178	_
Video Recognized	Correct
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2: *POSS WRITE HOMEWORK TE HOMEWORK	JOHN WRI
7: JOHN CAN GO *TOY GO CAN	JOHN CAN
12: JOHN *WHAT *WHAT CAN GO CAN	JOHN CAN
21: *SHOULD *NEW-YORK *FISH *WHO *CAR *CAR EAT CHICKEN	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	
25: JOHN *TELL *LOVE *WHO IX E IX IX	JOHN LIK
28: JOHN *WHO *WHO *LOVE E IX IX	JOHN LIK
30: JOHN *MARY *MARY *MARY E IX IX	JOHN LIK
36: MARY VEGETABLE *GIRL *GIVE *MARY *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1 40: JOHN *GO *GIRL MARY *MARY	JOHN IX
THINK MARY LOVE	301IIV 1X
43: JOHN *SHOULD BUY HOUSE	JOHN MUS
T BUY HOUSE	
50: *FRANK *SEE BUY CAR SHOULD	FUTURE J
OHN BUY CAR SHOULD  54: JOHN SHOULD *FUTURE BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE 57: JOHN *PREFER VISIT MARY IDE VISIT MARY	JOHN DEC
67: JOHN *YESTERDAY NOT BUY HOUSE  URE NOT BUY HOUSE	JOHN FUT
71: JOHN *FUTURE VISIT MARY	JOHN WIL
L VISIT MARY 74: JOHN *MARY VISIT MARY	JOHN NOT
VISIT MARY 77: *JOHN BLAME *LOVE	ANN BLAM
E MARY  84: *JOHN *BUY *HOMEWORK BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	JOHN TV
89: *FRANK *GIVE GIVE *THINK *GIVE NEW COAT GIVE MAN IX NEW COAT	JOHN IX

90: JOHN *GIVE1 IX SOMETHING-ONE WOMAN *ARRIVE	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK 92: JOHN GIVE *SOMETHING-ONE SOMETHING-ONE WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK  100: POSS NEW CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN 105: *FRANK *VEGETABLE	JOHN LEG
103. FRANK FVEGETABLE  107: JOHN *SUE FRIEND *GO *JOHN	JOHN POS
S FRIEND HAVE CANDY	
108: *GIVE1 *BOOK	WOMAN AR
RIVE 113: IX CAR BLUE *SOMETHING-ONE *BUY1	IX CAR B
LUE SUE BUY	IX CAN D
119: *PREFER *BUY1 *BLUE CAR *JANA	SUE BUY
IX CAR BLUE	
122: *SOMETHING-ONE READ BOOK	JOHN REA
D BOOK	
139: JOHN *BUY1 WHAT YESTERDAY BOOK	JOHN BUY
WHAT YESTERDAY BOOK	
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	10//5 70//
158: LOVE *WHO WHO N WHO	LOVE JOH
167: JOHN *SOMETHING-ONE *VEGETABLE LOVE MARY	JOHN IX
SAY LOVE MARY	
171: *SOMETHING-ONE *SOMETHING-ONE BLAME	JOHN MAR
Y BLAME	
174: PEOPLE GROUP GIVE1 *GIRL *WHAT	PEOPLE G
ROUP GIVE1 JANA TOY	JOHN ADD
181: *SUE ARRIVE IVE	JOHN ARR
184: *IX BOY *GIVE1 TEACHER *GIRL	ALL BOY
GIVE TEACHER APPLE	ALL DOT
189: JOHN *IX GIRL *BUY1	JOHN GIV
E GIRL BOX	
193: JOHN *GIVE3 *CORN BOX	JOHN GIV
E GIRL BOX	
199: *JOHN CHOCOLATE WHO	LIKE CHO
COLATE WHO 201: JOHN *SHOULD *WOMAN *WOMAN BUY HOUSE	JOHN TEI
L MARY IX-1P BUY HOUSE	JOHN TEL
running: ['norm-polar-rr', 'norm-rtheta', 'norm-polar-lr', 'norm	-nolar-lt
heta', 'delta-norm-polar-rr', 'delta-norm-rtheta', 'delta-norm-polar	•
<pre>lta-norm-polar-ltheta'] <class 'my_model_selectors.selectordic'=""></class></pre>	,
**** WER = 0.4044943820224719	
Total correct: 106 out of 178	
Video Recognized	Correct
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2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK	SOIN WILL
7: JOHN CAN GO *TOY	JOHN CAN
GO CAN	
12: JOHN *WHAT *GO1 CAN	JOHN CAN
GO CAN 21: JOHN FISH WONT *WHO BUT CAN *FUTURE CHICKEN	
	JOHN FIS

II LIONT FAT DUT CAN FAT CUTCKEN	
H WONT EAT BUT CAN EAT CHICKEN 25: JOHN LIKE IX *WHO IX	JOHN LIK
E IX IX IX	JOHN LIK
28: JOHN *WHO IX *WHO IX	JOHN LIK
E IX IX IX	
30: JOHN *MARY *MARY *MARY	JOHN LIK
E IX IX IX	
36: MARY VEGETABLE *GIRL *GIVE *MARY *MARY ETABLE KNOW IX LIKE CORN1	MARY VEG
40: JOHN *BILL *CORN MARY *MARY	JOHN IX
THINK MARY LOVE	JOHN IX
43: JOHN *POSS BUY HOUSE	JOHN MUS
T BUY HOUSE	
50: *JOHN *SEE BUY CAR *JOHN	FUTURE J
OHN BUY CAR SHOULD	
54: JOHN *JOHN *MARY BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	JOHN DEC
57: JOHN *PREFER VISIT MARY  IDE VISIT MARY	JOHN DEC
67: JOHN *YESTERDAY NOT BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	301111 1 0 1
71: JOHN *FUTURE VISIT MARY	JOHN WIL
L VISIT MARY	
74: *IX *MARY *MARY MARY	JOHN NOT
VISIT MARY	
77: *JOHN BLAME MARY	ANN BLAM
E MARY	TV 1D FT
84: *MARY *NEW *HOMEWORK BOOK  ND SOMETHING-ONE BOOK	IX-1P FI
89: *SAY *GIVE *MAN *OLD IX NEW COAT	JOHN IX
GIVE MAN IX NEW COAT	
90: JOHN *GIVE1 IX *IX WOMAN *ARRIVE	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
92: JOHN *MAN IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
100: POSS NEW CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN 105: JOHN *VEGETABLE	JOHN LEC
103. JOHN *VEGETABLE  107: JOHN *IX FRIEND *MARY *JOHN	JOHN LEG JOHN POS
S FRIEND HAVE CANDY	301114 1 03
108: *MAN *BOOK	WOMAN AR
RIVE	
113: IX CAR BLUE *MARY *BUY1	IX CAR B
LUE SUE BUY	
119: *MARY *BUY1 *BLUE CAR *MARY	SUE BUY
IX CAR BLUE	JOHN DEA
122: JOHN READ BOOK D BOOK	JOHN REA
139: JOHN *BUY1 WHAT YESTERDAY BOOK	JOHN BUY
WHAT YESTERDAY BOOK	301111 201
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	
158: LOVE JOHN WHO	LOVE JOH
N WHO	70131 =::
167: JOHN *TOY1 *MARY LOVE MARY	JOHN IX
SAY LOVE MARY	
171: JOHN *JOHN BLAME	JOHN MAR

Y BLAME	
174: PEOPLE GROUP GIVE1 *CORN TOY	PEOPLE G
ROUP GIVE1 JANA TOY	
181: *SUE ARRIVE	JOHN ARR
IVE 184: ALL BOY *GIVE1 TEACHER *GIRL	ALL BOY
GIVE TEACHER APPLE	ALL DOT
189: JOHN *SELF *CORN *BUY1	JOHN GIV
E GIRL BOX	
193: JOHN *GIVE1 *GIVE BOX	JOHN GIV
E GIRL BOX 199: *JOHN CHOCOLATE WHO	LIKE CHO
COLATE WHO	LIKE CHO
201: JOHN *MARY *WOMAN *JOHN BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	
running: ['norm-polar-rr', 'norm-rtheta', 'norm-polar-lr', 'norm heta', 'delta-norm-polar-rr', 'delta-norm-rtheta', 'delta-norm-polar lta-norm-polar-ltheta'] <class 'my_model_selectors.selectorcv'=""></class>	
**** WER = 0.4550561797752809	
Total correct: 97 out of 178	
Video Recognized	Correct
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2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK	
7: JOHN CAN GO CAN	JOHN CAN
GO CAN	TOUR CAN
12: JOHN *WHAT *WHAT CAN GO CAN	JOHN CAN
21: JOHN FISH WONT *WHO BUT *CAR *FUTURE CHICKEN	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	
25: JOHN LIKE *LOVE *MARY IX	JOHN LIK
E IX IX IX	JOHN LTV
28: JOHN *MARY *MARY IX E IX IX	JOHN LIK
30: JOHN *MARY *MARY IX	JOHN LIK
E IX IX IX	
36: MARY *MARY *GIRL *GIVE2 *MARY *JOHN	MARY VEG
ETABLE KNOW IX LIKE CORN1	JOHN TV
40: JOHN IX *CORN *JOHN *MARY THINK MARY LOVE	JOHN IX
43: JOHN *SHOULD BUY HOUSE	JOHN MUS
T BUY HOUSE	
50: *JOHN JOHN BUY CAR SHOULD	FUTURE J
OHN BUY CAR SHOULD	701111 6110
54: JOHN *JOHN *MARY BUY HOUSE ULD NOT BUY HOUSE	JOHN SHO
57: JOHN *MARY VISIT MARY	JOHN DEC
IDE VISIT MARY	00 220
67: JOHN *YESTERDAY *WHO BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	701111 777
71: JOHN *GIVE1 VISIT MARY L VISIT MARY	JOHN WIL
74: JOHN *MARY VISIT *IX	JOHN NOT
VISIT MARY	
77: *JOHN BLAME MARY	ANN BLAM

F MARY	
84: *FRANK *NEW *HOMEWORK BOOK	IX-1P FI
ND SOMETHING-ONE BOOK  89: JOHN *GIVE GIVE *SELF *GIVE NEW COAT	JOHN IX
GIVE MAN IX NEW COAT  90: JOHN *GIVE1 *GIVE1 SOMETHING-ONE WOMAN *ARRIVE	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK 92: JOHN GIVE IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK  100: POSS NEW CAR BREAK-DOWN  CAR DREAK DOWN	POSS NEW
CAR BREAK-DOWN 105: JOHN *VEGETABLE 107: JOHN *SUE FRIEND *GO *MARY	JOHN LEG
S FRIEND HAVE CANDY	JUNIN PUS
108: *FRANK *BOOK RIVE	WOMAN AR
113: *JOHN CAR BLUE *JOHN *BUY1 LUE SUE BUY	IX CAR B
119: *JOHN *BUY1 *BLUE *TOY *JANA IX CAR BLUE	SUE BUY
122: JOHN *HOUSE BOOK	JOHN REA
D BOOK 139: JOHN *BUY1 WHAT YESTERDAY *ARRIVE	JOHN BUY
WHAT YESTERDAY BOOK	JOHN DOT
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK 158: LOVE *SOMETHING-ONE WHO	LOVE JOH
N WHO	LOVE JOH
167: JOHN *TOY1 *MARY LOVE *PUTASIDE	JOHN IX
SAY LOVE MARY	TOUR MAD
171: JOHN *JOHN BLAME Y BLAME	JOHN MAR
174: *LIVE GROUP GIVE1 *CORN TOY	PEOPLE G
ROUP GIVE1 JANA TOY	
181: *SUE *VIDEOTAPE	JOHN ARR
IVE	ALL DOV
184: ALL BOY *GO TEACHER *CORN GIVE TEACHER APPLE	ALL BOY
189: JOHN *JANA *CORN *BUY1	JOHN GIV
E GIRL BOX	
193: JOHN *GIVE1 *CORN BOX	JOHN GIV
E GIRL BOX 199: *JOHN *ARRIVE *MARY	LIKE CHO
COLATE WHO	JOHN TEL
201: JOHN *MARY *WOMAN *WOMAN BUY HOUSE L MARY IX-1P BUY HOUSE	JOHN TEL
running: ['dist-norm-left-right', 'delta-dist-norm-left-right', rm-rx', 'delta-norm-ry', 'delta-norm-lx', 'delta-norm-ly', 'norm-point-ltheta', 'norm-polar-lr', 'norm-polar-ltheta', 'delta-norm-polar-lr', 'delta-norm-polar-ltheta', 'delta-norm-polar-lr', 'delta-norm-polar-ltheta', 'delta-norm-polar-ltheta-norm-polar-ltheta-norm-polar-ltheta-norm-polar-ltheta-norm-polar-ltheta-norm-polar-lthet	lar-rr', olar-rr',
**** WER = 0.46629213483146065	
Total correct: 95 out of 178	6
Video Recognized	Correct

2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK 7: JOHN *CAR *BLUE *CAR	JOHN CAN
GO CAN	
12: JOHN CAN *GO1 CAN	JOHN CAN
GO CAN 21: JOHN *JOHN WONT *TELL *CAR *CAR *FUTURE *JOHN	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	JOHN F13
25: JOHN *WHO *THROW IX *THROW	JOHN LIK
E IX IX IX	701111 1 71/
28: JOHN *TELL *BILL IX IX E IX IX IX	JOHN LIK
30: JOHN *MARY *MARY *JOHN IX	JOHN LIK
E IX IX IX	
36: MARY *WHO *IX *GIVE *MARY *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1  40: JOHN IX *JOHN MARY *MARY	JOHN IX
THINK MARY LOVE	30111V 17X
43: JOHN *POSS BUY HOUSE	JOHN MUS
T BUY HOUSE	
50: *JOHN *SEE BUY CAR *JOHN	FUTURE J
OHN BUY CAR SHOULD 54: JOHN *JOHN *MARY BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	JOHN JHO
57: *MARY *MARY *IX *IX	JOHN DEC
IDE VISIT MARY	
67: JOHN FUTURE NOT BUY HOUSE URE NOT BUY HOUSE	JOHN FUT
	701111 1171
71: JOHN WILL *GO MARY	JOHN WIL
71: JOHN WILL *GO MARY L VISIT MARY	JOHN WIL
L VISIT MARY 74: JOHN *MARY *MARY MARY	JOHN WIL
L VISIT MARY 74: JOHN *MARY *MARY MARY VISIT MARY	JOHN NOT
L VISIT MARY 74: JOHN *MARY *MARY MARY VISIT MARY 77: *JOHN BLAME MARY	
L VISIT MARY 74: JOHN *MARY *MARY MARY VISIT MARY 77: *JOHN BLAME MARY E MARY	JOHN NOT
L VISIT MARY 74: JOHN *MARY *MARY MARY VISIT MARY 77: *JOHN BLAME MARY	JOHN NOT
L VISIT MARY 74: JOHN *MARY *MARY MARY VISIT MARY 77: *JOHN BLAME MARY E MARY 84: *JOHN *NEW *YESTERDAY *NEW ND SOMETHING-ONE BOOK 89: *WHO IX *IX *THROW IX NEW COAT	JOHN NOT
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L VISIT MARY 74: JOHN *MARY *MARY MARY VISIT MARY 77: *JOHN BLAME MARY  E MARY 84: *JOHN *NEW *YESTERDAY *NEW  ND SOMETHING-ONE BOOK 89: *WHO IX *IX *THROW IX NEW COAT  GIVE MAN IX NEW COAT 90: JOHN *IX IX *IX *IX BOOK  E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX IX *IX WOMAN *HOUSE  E IX SOMETHING-ONE WOMAN BOOK 100: POSS NEW CAR BREAK-DOWN CAR BREAK-DOWN	JOHN NOT  ANN BLAM  IX-1P FI  JOHN IX  JOHN GIV  JOHN GIV  POSS NEW
L VISIT MARY 74: JOHN *MARY *MARY MARY VISIT MARY 77: *JOHN BLAME MARY  E MARY 84: *JOHN *NEW *YESTERDAY *NEW  ND SOMETHING-ONE BOOK 89: *WHO IX *IX *THROW IX NEW COAT GIVE MAN IX NEW COAT 90: JOHN *IX IX *IX *IX BOOK  E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX IX *IX WOMAN *HOUSE  E IX SOMETHING-ONE WOMAN BOOK 100: POSS NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *WHO	JOHN NOT  ANN BLAM  IX-1P FI  JOHN IX  JOHN GIV  JOHN GIV  POSS NEW  JOHN LEG
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L VISIT MARY 74: JOHN *MARY *MARY MARY VISIT MARY 77: *JOHN BLAME MARY E MARY 84: *JOHN *NEW *YESTERDAY *NEW ND SOMETHING-ONE BOOK 89: *WHO IX *IX *THROW IX NEW COAT GIVE MAN IX NEW COAT 90: JOHN *IX IX *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX IX *IX WOMAN *HOUSE E IX SOMETHING-ONE WOMAN BOOK 100: POSS NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *WHO 107: *MARY *IX FRIEND HAVE *JOHN S FRIEND HAVE CANDY 108: *IX ARRIVE RIVE	JOHN NOT  ANN BLAM  IX-1P FI  JOHN IX  JOHN GIV  JOHN GIV  POSS NEW  JOHN LEG JOHN POS  WOMAN AR
L VISIT MARY 74: JOHN *MARY *MARY MARY VISIT MARY 77: *JOHN BLAME MARY  E MARY 84: *JOHN *NEW *YESTERDAY *NEW  ND SOMETHING-ONE BOOK 89: *WHO IX *IX *THROW IX NEW COAT  GIVE MAN IX NEW COAT 90: JOHN *IX IX *IX *IX BOOK  E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX IX *IX WOMAN *HOUSE  E IX SOMETHING-ONE WOMAN BOOK 100: POSS NEW CAR BREAK-DOWN  CAR BREAK-DOWN 105: JOHN *WHO 107: *MARY *IX FRIEND HAVE *JOHN  S FRIEND HAVE CANDY 108: *IX ARRIVE  RIVE 113: *JOHN CAR *JOHN *MARY *BUY1	JOHN NOT  ANN BLAM  IX-1P FI  JOHN IX  JOHN GIV  POSS NEW  JOHN LEG JOHN POS
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L VISIT MARY  74: JOHN *MARY *MARY MARY  VISIT MARY  77: *JOHN BLAME MARY  E MARY  84: *JOHN *NEW *YESTERDAY *NEW  ND SOMETHING-ONE BOOK  89: *WHO IX *IX *THROW IX NEW COAT  GIVE MAN IX NEW COAT  90: JOHN *IX IX *IX *IX BOOK  E IX SOMETHING-ONE WOMAN BOOK  92: JOHN *IX IX *IX WOMAN *HOUSE  E IX SOMETHING-ONE WOMAN BOOK  100: POSS NEW CAR BREAK-DOWN  CAR BREAK-DOWN  105: JOHN *WHO  107: *MARY *IX FRIEND HAVE *JOHN  S FRIEND HAVE CANDY  108: *IX ARRIVE  RIVE  113: *JOHN CAR *JOHN *MARY *BUY1  LUE SUE BUY  119: *MARY *BUY1 IX CAR *APPLE  IX CAR BLUE  122: JOHN READ *COAT	JOHN NOT  ANN BLAM  IX-1P FI  JOHN IX  JOHN GIV  POSS NEW  JOHN LEG JOHN POS  WOMAN AR  IX CAR B
L VISIT MARY 74: JOHN *MARY *MARY MARY VISIT MARY 77: *JOHN BLAME MARY  E MARY 84: *JOHN *NEW *YESTERDAY *NEW  ND SOMETHING-ONE BOOK 89: *WHO IX *IX *THROW IX NEW COAT GIVE MAN IX NEW COAT 90: JOHN *IX IX *IX BOOK  E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX IX *IX WOMAN *HOUSE  E IX SOMETHING-ONE WOMAN BOOK 100: POSS NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *WHO 107: *MARY *IX FRIEND HAVE *JOHN  S FRIEND HAVE CANDY 108: *IX ARRIVE RIVE  113: *JOHN CAR *JOHN *MARY *BUY1 LUE SUE BUY 119: *MARY *BUY1 IX CAR *APPLE IX CAR BLUE 122: JOHN READ *COAT D BOOK	JOHN NOT ANN BLAM IX-1P FI JOHN IX JOHN GIV JOHN GIV POSS NEW JOHN LEG JOHN POS WOMAN AR IX CAR B SUE BUY JOHN REA
L VISIT MARY  74: JOHN *MARY *MARY MARY  VISIT MARY  77: *JOHN BLAME MARY  E MARY  84: *JOHN *NEW *YESTERDAY *NEW  ND SOMETHING-ONE BOOK  89: *WHO IX *IX *THROW IX NEW COAT  GIVE MAN IX NEW COAT  90: JOHN *IX IX *IX *IX BOOK  E IX SOMETHING-ONE WOMAN BOOK  92: JOHN *IX IX *IX WOMAN *HOUSE  E IX SOMETHING-ONE WOMAN BOOK  100: POSS NEW CAR BREAK-DOWN  CAR BREAK-DOWN  105: JOHN *WHO  107: *MARY *IX FRIEND HAVE *JOHN  S FRIEND HAVE CANDY  108: *IX ARRIVE  RIVE  113: *JOHN CAR *JOHN *MARY *BUY1  LUE SUE BUY  119: *MARY *BUY1 IX CAR *APPLE  IX CAR BLUE  122: JOHN READ *COAT	JOHN NOT  ANN BLAM  IX-1P FI  JOHN IX  JOHN GIV  POSS NEW  JOHN LEG JOHN POS  WOMAN AR  IX CAR B  SUE BUY

142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK 158: LOVE JOHN WHO	LOVE JOH
N WHO 167: JOHN *JOHN *MARY LOVE MARY	JOHN IX
SAY LOVE MARY 171: *MARY *JOHN BLAME	JOHN MAR
Y BLAME 174: PEOPLE GROUP GIVE1 *JOHN *WHAT	PEOPLE G
ROUP GIVE1 JANA TOY 181: *SUE ARRIVE	JOHN ARR
IVE 184: ALL BOY *GIVE1 TEACHER APPLE	ALL BOY
GIVE TEACHER APPLE 189: *MARY *IX *CORN BOX	JOHN GIV
E GIRL BOX 193: JOHN *IX GIRL BOX	JOHN GIV
E GIRL BOX 199: *JOHN CHOCOLATE WHO	LIKE CHO
COLATE WHO 201: JOHN *JOHN *LOVE *JOHN BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSErunning: ['dist-norm-left-right', 'delta-dist-norm-left-right', rm-rx', 'delta-norm-ry', 'delta-norm-lx', 'delta-norm-ly', 'norm-po 'norm-rtheta', 'norm-polar-lr', 'norm-polar-ltheta', 'delta-norm-p 'delta-norm-rtheta', 'delta-norm-polar-lr', 'delta-norm-polar-lthe s 'my_model_selectors.SelectorBIC'>	lar-rr', olar-rr',
**** WER = 0.5280898876404494	
Total correct: 84 out of 178 Video Recognized	Correct
Total correct: 84 out of 178	
Total correct: 84 out of 178  Video Recognized  ===================================	
Total correct: 84 out of 178  Video Recognized	=======
Total correct: 84 out of 178  Video Recognized  ===================================	JOHN WRI
Total correct: 84 out of 178  Video Recognized	JOHN WRI
Total correct: 84 out of 178  Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN
Total correct: 84 out of 178  Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS
Total correct: 84 out of 178  Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK
Total correct: 84 out of 178  Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK
Total correct: 84 out of 178  Video Recognized	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK  JOHN LIK
Total correct: 84 out of 178  Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK  JOHN LIK  MARY VEG
Total correct: 84 out of 178  Video Recognized  ===================================	JOHN WRI  JOHN CAN  JOHN FIS  JOHN LIK  JOHN LIK  JOHN LIK  MARY VEG  JOHN IX

57: JOHN *MARY *IX *IX IDE VISIT MARY	JOHN DEC
67: JOHN *IX *WHO BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN *FUTURE VISIT *GIVE1	JOHN WIL
L VISIT MARY	
74: *MARY *MARY MARY MARY	JOHN NOT
VISIT MARY 77: *IX BLAME *IX	ANN BLAM
F MARY	ANN DLAM
84: *ARRIVE *GIVE1 *YESTERDAY BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	
89: *THINK IX *IX *SEARCH-FOR IX *BOOK COAT	JOHN IX
GIVE MAN IX NEW COAT	
90: *MARY *IX IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	70111 671
92: JOHN *IX IX *IX *IX BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK 100: POSS NEW CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	PO33 NEW
105: JOHN *WHO	JOHN LEG
107: *MARY POSS *ARRIVE *IX *MARY	JOHN POS
S FRIEND HAVE CANDY	
108: *IX *BOOK	WOMAN AR
RIVE	
113: *JOHN CAR *CAR *MARY *BUY1	IX CAR B
LUE SUE BUY	CHE DIN
119: *MARY *BUY1 IX CAR *IX IX CAR BLUE	SUE BUY
122: JOHN *CAR *HOUSE	JOHN REA
D BOOK	JOHN KEA
139: JOHN *BUY1 WHAT YESTERDAY BOOK	JOHN BUY
WHAT YESTERDAY BOOK	
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	
158: LOVE *IX *MARY	LOVE JOH
N WHO	JOHN IX
167: *MARY IX *MARY LOVE *IX SAY LOVE MARY	JOHN IX
171: *MARY *JOHN BLAME	JOHN MAR
Y BLAME	
174: *GIVE1 GROUP GIVE1 *MARY *CAR	PEOPLE G
ROUP GIVE1 JANA TOY	
181: *SUE ARRIVE	JOHN ARR
IVE	
184: *IX BOY *GIVE1 TEACHER *CORN	ALL BOY
GIVE TEACHER APPLE 189: *MARY *IX *CORN *WHAT	JOHN GIV
E GIRL BOX	JOINT GIV
193: JOHN *IX GIRL BOX	JOHN GIV
E GIRL BOX	
199: *IX CHOCOLATE WHO	LIKE CHO
COLATE WHO	
201: JOHN *FUTURE *WOMAN *IX BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	'dol+2 ==
running: ['dist-norm-left-right', 'delta-dist-norm-left-right', rm-rx', 'delta-norm-ry', 'delta-norm-lx', 'delta-norm-ly', 'norm-pol	
derea normany, derea normany, derea normany, norm-po-	

'norm-rtheta', 'norm-polar-lr', 'norm-polar-ltheta', 'delta-norm-polar-rr', 'delta-norm-rtheta', 'delta-norm-polar-lr', 'delta-norm-polar-ltheta'] <clas s 'my\_model\_selectors.SelectorDIC'>

### \*\*\*\* WER = 0.46629213483146065 Total correct: 95 out of 178

Total correct: 95 out of 178	Connect
Video Recognized	Correct
2: JOHN WRITE *ARRIVE	JOHN WRI
TE HOMEWORK 7: JOHN *CAR GO CAN	JOHN CAN
GO CAN	JOHN CAN
12: JOHN CAN *GO1 CAN	JOHN CAN
GO CAN	
21: JOHN *JOHN WONT *WHO *CAR *CAR *FUTURE *MARY	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	
25: *ANN *IX *MARY IX *THROW	JOHN LIK
E IX IX IX	
28: JOHN *WHO *BILL IX IX	JOHN LIK
E IX IX IX	JOHN LTV
30: JOHN *MARY *MARY IX E IX IX IX	JOHN LIK
36: MARY *JOHN *YESTERDAY *GIVE *MARY *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1	HART VEG
40: JOHN *GIVE *JOHN MARY *MARY	JOHN IX
THINK MARY LOVE	
43: JOHN *VISIT BUY HOUSE	JOHN MUS
T BUY HOUSE	
50: *JOHN *SEE BUY CAR *JOHN	FUTURE J
OHN BUY CAR SHOULD	
54: JOHN *JOHN *MARY BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	JOHN DEC
57: JOHN *JOHN *IX *GIVE IDE VISIT MARY	JOHN DEC
67: JOHN *IX NOT BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	301114 1 0 1
71: JOHN *FUTURE VISIT MARY	JOHN WIL
L VISIT MARY	
74: JOHN *MARY *MARY MARY	JOHN NOT
VISIT MARY	
77: *JOHN BLAME MARY	ANN BLAM
E MARY	
84: *JOHN *JOHN *YESTERDAY BOOK	IX-1P FI
ND SOMETHING-ONE BOOK 89: JOHN IX GIVE *THROW IX *BUY COAT	JOHN IX
GIVE MAN IX NEW COAT	JOHN IX
90: JOHN *IX IX *GIVE WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
92: JOHN *WOMAN IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
100: POSS NEW CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	
105: JOHN *VEGETABLE	JOHN LEG
107: JOHN *IX *ARRIVE *MARY *JOHN	JOHN POS
S FRIEND HAVE CANDY	LIOMANI AD
108: WOMAN *BOOK	WOMAN AR

DTVE	
RIVE 113: *JOHN CAR *JOHN *JOHN *BUY1	IX CAR B
LUE SUE BUY 119: *JOHN *BUY1 IX CAR *IX	SUE BUY
IX CAR BLUE	
122: JOHN *CAR BOOK D BOOK	JOHN REA
139: JOHN *BUY1 WHAT *WHAT BOOK WHAT YESTERDAY BOOK	JOHN BUY
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	10//5 7011
158: LOVE JOHN WHO N WHO	LOVE JOH
167: JOHN *JOHN LOVE MARY	JOHN IX
SAY LOVE MARY 171: *MARY *JOHN BLAME	JOHN MAD
Y BLAME	JOHN MAR
174: *CAR GROUP GIVE1 *JOHN *WHAT	PEOPLE G
ROUP GIVE1 JANA TOY	JOHN ADD
181: *SUE ARRIVE IVE	JOHN ARR
184: ALL BOY *GIVE1 TEACHER APPLE GIVE TEACHER APPLE	ALL BOY
189: JOHN *JOHN *WHAT	JOHN GIV
E GIRL BOX	JOHN CTV
193: JOHN *POSS *CORN BOX E GIRL BOX	JOHN GIV
199: *JOHN CHOCOLATE *MARY	LIKE CHO
COLATE WHO 201: JOHN *JOHN MARY *JOHN BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSErunning: ['dist-norm-left-right', 'delta-dist-norm-left-right', rm-rx', 'delta-norm-ry', 'delta-norm-lx', 'delta-norm-ly', 'norm-pol 'norm-rtheta', 'norm-polar-lr', 'norm-polar-ltheta', 'delta-norm-pol 'delta-norm-rtheta', 'delta-norm-polar-lr', 'delta-norm-polar-lthet s 'my_model_selectors.SelectorCV'>	lar-rr', olar-rr',
s my_moder_serectors.serectorcv /	
**** WER = 0.4943820224719101	
Total correct: 90 out of 178 Video Recognized	Correct
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2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK 7: JOHN *TOY GO *TOY	JOHN CAN
GO CAN 12: JOHN *CAR *GO1 CAN	JOHN CAN
GO CAN	
21: JOHN *HOMEWORK WONT *JOHN *CAR *WHAT *FUTURE *MARY H WONT EAT BUT CAN EAT CHICKEN	JOHN FIS
25: JOHN *IX *MARY *MARY IX E IX IX	JOHN LIK
28: JOHN *IX *MARY IX IX E IX IX IX	JOHN LIK
30: JOHN *MARY *MARY IX IX	JOHN LIK
E IX IX 36: MARY *JOHN *YESTERDAY *GIVE2 *MARY *JOHN	MARY VEG

ETABLE KNOW IX LIKE CORN1	
40: JOHN IX *JOHN MARY *MARY	JOHN IX
THINK MARY LOVE	
43: JOHN *JOHN BUY HOUSE	JOHN MUS
T BUY HOUSE	
50: *JOHN JOHN BUY CAR *HOMEWORK	FUTURE J
OHN BUY CAR SHOULD 54: JOHN *JOHN *MARY BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	JOHN JHO
57: *MARY *JOHN VISIT *IX	JOHN DEC
IDE VISIT MARY	
67: JOHN *IX *JOHN BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	701111 1171
71: JOHN *FUTURE VISIT MARY L VISIT MARY	JOHN WIL
74: JOHN *MARY *MARY MARY	JOHN NOT
VISIT MARY	301
77: *JOHN BLAME MARY	ANN BLAM
E MARY	
84: *JOHN *WRITE *HOMEWORK BOOK	IX-1P FI
ND SOMETHING-ONE BOOK 89: JOHN IX *IX *SEARCH-FOR IX *WRITE COAT	JOHN IX
GIVE MAN IX NEW COAT	JOHN IX
90: JOHN *GIVE1 *GIVE1 SOMETHING-ONE WOMAN *FRIEND	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
92: JOHN *SEARCH-FOR IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
100: POSS *WRITE CAR BREAK-DOWN  CAR BREAK-DOWN	POSS NEW
CAR BREAK-DUWN	
	JOHN LEG
105: JOHN *VEGETABLE	JOHN LEG
105: JOHN *VEGETABLE 107: *MARY *JOHN FRIEND *MARY *MARY	
105: JOHN *VEGETABLE 107: *MARY *JOHN FRIEND *MARY *MARY  S FRIEND HAVE CANDY 108: WOMAN *BOOK RIVE	JOHN POS WOMAN AR
105: JOHN *VEGETABLE 107: *MARY *JOHN FRIEND *MARY *MARY  S FRIEND HAVE CANDY 108: WOMAN *BOOK  RIVE 113: *JOHN CAR *MARY *MARY *BUY1	JOHN POS
105: JOHN *VEGETABLE 107: *MARY *JOHN FRIEND *MARY *MARY  S FRIEND HAVE CANDY 108: WOMAN *BOOK  RIVE 113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY	JOHN POS WOMAN AR IX CAR B
105: JOHN *VEGETABLE 107: *MARY *JOHN FRIEND *MARY *MARY  S FRIEND HAVE CANDY 108: WOMAN *BOOK  RIVE 113: *JOHN CAR *MARY *MARY *BUY1	JOHN POS WOMAN AR
105: JOHN *VEGETABLE 107: *MARY *JOHN FRIEND *MARY *MARY  S FRIEND HAVE CANDY 108: WOMAN *BOOK  RIVE 113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY 119: *MARY *BUY1 *WHAT CAR *OLD	JOHN POS WOMAN AR IX CAR B
105: JOHN *VEGETABLE 107: *MARY *JOHN FRIEND *MARY *MARY  S FRIEND HAVE CANDY 108: WOMAN *BOOK  RIVE 113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY 119: *MARY *BUY1 *WHAT CAR *OLD IX CAR BLUE	JOHN POS WOMAN AR IX CAR B SUE BUY
105: JOHN *VEGETABLE 107: *MARY *JOHN FRIEND *MARY *MARY  S FRIEND HAVE CANDY 108: WOMAN *BOOK  RIVE 113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY 119: *MARY *BUY1 *WHAT CAR *OLD  IX CAR BLUE 122: JOHN *CAR BOOK  D BOOK 139: JOHN *BUY1 WHAT *WHAT *FRIEND	JOHN POS WOMAN AR IX CAR B SUE BUY
105: JOHN *VEGETABLE 107: *MARY *JOHN FRIEND *MARY *MARY  S FRIEND HAVE CANDY 108: WOMAN *BOOK  RIVE 113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY 119: *MARY *BUY1 *WHAT CAR *OLD  IX CAR BLUE 122: JOHN *CAR BOOK  D BOOK 139: JOHN *BUY1 WHAT *WHAT *FRIEND WHAT YESTERDAY BOOK	JOHN POS WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY
105: JOHN *VEGETABLE 107: *MARY *JOHN FRIEND *MARY *MARY  S FRIEND HAVE CANDY 108: WOMAN *BOOK  RIVE 113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY 119: *MARY *BUY1 *WHAT CAR *OLD  IX CAR BLUE 122: JOHN *CAR BOOK  D BOOK 139: JOHN *BUY1 WHAT *WHAT *FRIEND WHAT YESTERDAY BOOK 142: JOHN BUY YESTERDAY WHAT BOOK	JOHN POS WOMAN AR IX CAR B SUE BUY JOHN REA
105: JOHN *VEGETABLE 107: *MARY *JOHN FRIEND *MARY *MARY  S FRIEND HAVE CANDY 108: WOMAN *BOOK  RIVE 113: *JOHN CAR *MARY *MARY *BUY1  LUE SUE BUY 119: *MARY *BUY1 *WHAT CAR *OLD  IX CAR BLUE 122: JOHN *CAR BOOK  D BOOK 139: JOHN *BUY1 WHAT *WHAT *FRIEND  WHAT YESTERDAY BOOK 142: JOHN BUY YESTERDAY WHAT BOOK  YESTERDAY WHAT BOOK	JOHN POS WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY
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E GIRL BOX 193: JOHN \*YESTERDAY GIRL BOX JOHN GIV E GIRL BOX 199: \*JOHN CHOCOLATE \*MARY LIKE CHO COLATE WHO 201: JOHN \*GIVE \*LOVE \*JOHN BUY HOUSE JOHN TEL L MARY IX-1P BUY HOUSE ----running: ['norm-rx', 'norm-ry', 'norm-lx', 'norm-ly', 'dist-norm-left-rig ht', 'delta-dist-norm-left-right', 'delta-norm-rx', 'delta-norm-ry', 'delta-n orm-lx', 'delta-norm-ly', 'norm-polar-rr', 'norm-rtheta', 'norm-polar-lr', 'n orm-polar-ltheta', 'delta-norm-polar-rr', 'delta-norm-rtheta', 'delta-norm-po lar-lr', 'delta-norm-polar-ltheta'] <class 'my\_model\_selectors.SelectorConsta</pre> nt'> \*\*\*\* WER = 0.4550561797752809 Total correct: 97 out of 178 Video Recognized Correct \_\_\_\_\_\_ 2: JOHN WRITE HOMEWORK JOHN WRI TE HOMEWORK 7: JOHN \*CAR \*HAVE \*CAR JOHN CAN GO CAN 12: JOHN CAN \*GO1 CAN JOHN CAN GO CAN 21: JOHN \*NEW \*VISIT \*MARY \*CAR \*CAR \*FUTURE \*JOHN JOHN FIS H WONT EAT BUT CAN EAT CHICKEN 25: \*IX \*IX IX \*LIKE IX JOHN LIK E IX IX IX 28: \*ANN \*MARY IX IX IX JOHN LIK E IX IX IX 30: JOHN LIKE \*MARY \*LIKE IX JOHN LIK E IX IX IX 36: MARY \*JOHN \*GIRL \*GIVE \*MARY \*MARY MARY VEG ETABLE KNOW IX LIKE CORN1 40: JOHN IX \*CORN MARY \*MARY JOHN IX THINK MARY LOVE 43: JOHN \*IX BUY HOUSE JOHN MUS T BUY HOUSE 50: \*POSS \*SEE BUY CAR \*IX FUTURE J OHN BUY CAR SHOULD 54: JOHN \*JOHN NOT BUY HOUSE JOHN SHO ULD NOT BUY HOUSE 57: JOHN \*JOHN \*IX \*IX JOHN DEC IDE VISIT MARY 67: JOHN FUTURE NOT BUY HOUSE JOHN FUT URE NOT BUY HOUSE 71: JOHN \*FUTURE VISIT MARY JOHN WIL L VISIT MARY 74: JOHN \*MARY \*MARY MARY JOHN NOT VISIT MARY 77: \*IX BLAME MARY ANN BLAM E MARY 84: \*IX \*ARRIVE \*VISIT BOOK IX-1P FI ND SOMETHING-ONE BOOK 89: JOHN IX \*IX \*GO IX NEW COAT JOHN IX

GIVE MAN IX NEW COAT

90: *MARY *GIVE1 IX *IX WOMAN BOOK	JOHN GIV
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105: JOHN *SEE	JOHN LEG
107: JOHN *IX *CAR HAVE *JOHN S FRIEND HAVE CANDY	JOHN POS
108: *LOVE *BOOK RIVE	WOMAN AR
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D BOOK	JOHN KEA
139: JOHN *BUY1 WHAT YESTERDAY BOOK WHAT YESTERDAY BOOK	JOHN BUY
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	
158: LOVE *MARY WHO	LOVE JOH
N WHO	
167: JOHN IX *LEAVE LOVE MARY	JOHN IX
SAY LOVE MARY	
171: *MARY *JOHN BLAME	JOHN MAR
Y BLAME	
174: *CAR *GIVE1 GIVE1 *WHO *CAN	PEOPLE G
ROUP GIVE1 JANA TOY	
181: JOHN *BOX	JOHN ARR
IVE	
184: *IX BOY *GIVE1 TEACHER APPLE	ALL BOY
GIVE TEACHER APPLE	
189: JOHN *SEE GIRL *CAR	JOHN GIV
E GIRL BOX	
193: JOHN *SEE GIRL BOX	JOHN GIV
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199: *JOHN CHOCOLATE *MARY	LIKE CHO
COLATE WHO	JOHN TEL
201: JOHN *THINK *WOMAN *LIKE BUY HOUSE L MARY IX-1P BUY HOUSE	JOHN TEL
running: ['norm-rx', 'norm-ry', 'norm-lx', 'norm-ly', 'dist-norm ht', 'delta-dist-norm-left-right', 'delta-norm-rx', 'delta-norm-ry', orm-lx', 'delta-norm-ly', 'norm-polar-rr', 'norm-rtheta', 'norm-pola orm-polar-ltheta', 'delta-norm-polar-rr', 'delta-norm-rtheta', 'delta-lr', 'delta-norm-polar-ltheta'] <class 'my_model_selectors.selectors.<="" td=""><td>'delta-n r-lr', 'n a-norm-po</td></class>	'delta-n r-lr', 'n a-norm-po
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2: *MARY WRITE *ARRIVE	JOHN WRI
TE HOMEWORK	
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GO CAN	
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25: JOHN *MARY *MARY *LIKE *LOVE	JOHN LIK
E IX IX IX 28: JOHN LIKE *MARY *MARY *LOVE	JOHN LIK
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30: JOHN LIKE *MARY *MARY IX	JOHN LIK
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36: MARY *WHO *GIVE3 *WOMAN LIKE *MARY ETABLE KNOW IX LIKE CORN1	MARY VEG
40: *MARY *MARY *CORN *VEGETABLE *MARY	JOHN IX
THINK MARY LOVE	
43: JOHN *SHOULD BUY HOUSE T BUY HOUSE	JOHN MUS
50: FUTURE *SEE BUY CAR *MARY	FUTURE J
OHN BUY CAR SHOULD	
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ULD NOT BUY HOUSE	JOHN DEC
57: JOHN *MARY *GO MARY  IDE VISIT MARY	JOHN DEC
67: JOHN FUTURE NOT BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN *FUTURE VISIT MARY	JOHN WIL
L VISIT MARY 74: JOHN *MARY *MARY MARY	JOHN NOT
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SAY LOVE MARY 171: *MARY *JOHN BLAME	JOHN MAR
Y BLAME	JOHN MAR
174: *GIVE1 *GIVE1 GIVE1 *MARY *VISIT ROUP GIVE1 JANA TOY	PEOPLE G
181: JOHN *GIVE1	JOHN ARR
<pre>IVE    184: *IX *YESTERDAY *GIVE1 TEACHER APPLE</pre>	ALL BOY
GIVE TEACHER APPLE	
189: *JANA *GIVE3 *CORN *ARRIVE E GIRL BOX	JOHN GIV
193: JOHN *POSS *NOT BOX	JOHN GIV
E GIRL BOX	
199: *JOHN *ARRIVE WHO	LIKE CHO
COLATE WHO 201: JOHN *FUTURE MARY *LIKE BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	JOHN TEE
running: ['norm-rx', 'norm-ry', 'norm-lx', 'norm-ly', 'dist-norm	m-left-rig
ht', 'delta-dist-norm-left-right', 'delta-norm-rx', 'delta-norm-ry'	
orm-lx', 'delta-norm-ly', 'norm-polar-rr', 'norm-rtheta', 'norm-polar	
orm-polar-ltheta', 'delta-norm-polar-rr', 'delta-norm-rtheta', 'del	
<pre>lar-lr', 'delta-norm-polar-ltheta'] <class 'my_model_selectors.selectors.<="" pre=""></class></pre>	ctorDIC'>
hithirt 1150 0 150571157200000	
**** WER = 0.4606741573033708  Total correct: 96 out of 178	
Video Recognized	Correct
video	
=======================================	
2: JOHN WRITE *ARRIVE	JOHN WRI
TE HOMEWORK	
7: JOHN *CAR GO CAN	JOHN CAN
GO CAN	
12: JOHN CAN *GO1 CAN	JOHN CAN
GO CAN	
21: JOHN *JOHN *JOHN *JOHN *CAR *CAR *FUTURE *FUTURE	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	701N 1 T/
25: JOHN *IX *LOVE IX IX	JOHN LIK
E IX IX IX 28: *ANN *IX IX IX IX	JOHN LIK
E IX IX IX	JOHN LIK
30: *IX *MARY IX IX IX	JOHN LIK
E IX IX IX	
36: MARY *JOHN *GIVE3 *VISIT *JOHN *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1	
40: JOHN IX *JOHN MARY *IX	JOHN IX
THINK MARY LOVE	
43: JOHN *JOHN BUY HOUSE	JOHN MUS
T BUY HOUSE	FUTURE 3
50: *JOHN *SEE BUY CAR *JOHN	FUTURE J
OHN BUY CAR SHOULD 54: JOHN *FUTURE *FUTURE BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	JOHN JHO
57: *IX *MARY VISIT *IX	JOHN DEC
IDE VISIT MARY	-
67: JOHN FUTURE *MARY BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71. JOHN *FITHER VICIT MADV	JOHN LITE

JOHN WIL

71: JOHN \*FUTURE VISIT MARY

L VISIT MARY	
74: *IX *MARY *MARY MARY	JOHN NOT
VISIT MARY	
77: *JOHN BLAME MARY	ANN BLAM
E MARY	TV 1D FT
84: *JOHN *ARRIVE *CAR BOOK ND SOMETHING-ONE BOOK	IX-1P FI
89: JOHN IX *IX *IX NEW COAT	JOHN IX
GIVE MAN IX NEW COAT	30111 1X
90: *MARY *GIVE1 IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
92: JOHN *IX IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
100: POSS NEW CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	
105: JOHN *POSS	JOHN LEG
107: *MARY POSS *JOHN *IX *JOHN	JOHN POS
S FRIEND HAVE CANDY  108: *MARY *LOVE	WOMAN AR
RIVE	WUMAN AK
113: IX CAR *JOHN *JOHN *BUY1	IX CAR B
LUE SUE BUY	IX CAN D
119: *MARY *BUY1 IX *JOHN *IX	SUE BUY
IX CAR BLUE	
122: JOHN *HOUSE BOOK	JOHN REA
D BOOK	
139: *IX *BUY1 WHAT YESTERDAY BOOK	JOHN BUY
WHAT YESTERDAY BOOK	
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	
158: LOVE JOHN WHO	LOVE JOH
N WHO 167: JOHN IX *MARY LOVE MARY	JOHN IX
SAY LOVE MARY	JOHN IX
171: *MARY *JOHN BLAME	JOHN MAR
Y BLAME	JOHN HAR
174: *JOHN *GIVE1 GIVE1 *JOHN TOY	PEOPLE G
ROUP GIVE1 JANA TOY	
181: JOHN ARRIVE	JOHN ARR
IVE	
184: *IX BOY *GIVE1 TEACHER APPLE	ALL BOY
GIVE TEACHER APPLE	
189: JOHN *MARY *PREFER BOX	JOHN GIV
E GIRL BOX	JOHN CTV
193: JOHN *POSS *VISIT BOX E GIRL BOX	JOHN GIV
199: *JOHN *ARRIVE WHO	LIKE CHO
COLATE WHO	LIKE CHO
201: JOHN *GIVE1 *IX *LIKE BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	
running: ['norm-rx', 'norm-ry', 'norm-lx', 'norm-ly', 'dist-norm	-left-rig
<pre>ht', 'delta-dist-norm-left-right', 'delta-norm-rx', 'delta-norm-ry',</pre>	
orm-lx', 'delta-norm-ly', 'norm-polar-rr', 'norm-rtheta', 'norm-pola	
orm-polar-ltheta', 'delta-norm-polar-rr', 'delta-norm-rtheta', 'delt	
<pre>lar-lr', 'delta-norm-polar-ltheta'] <class 'my_model_selectors.selectors.<="" pre=""></class></pre>	toruv'>

Total correct: 88 out of 178

Video Recognized	Correct
2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK 7: JOHN *TOY GO CAN	JOHN CAN
GO CAN 12: JOHN CAN *WHAT CAN	JOHN CAN
GO CAN 21: JOHN *HOMEWORK *HOMEWORK *JOHN *CAR *CAR *FUTURE *HOMEWORK	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN  25: *ANN *IX *ANN IX *ANN	JOHN LIK
E IX IX IX	
28: JOHN *MARY IX *ANN IX E IX IX IX	JOHN LIK
30: *IX *IX IX IX IX E IX IX	JOHN LIK
36: MARY *JOHN *YESTERDAY IX *MARY *IX ETABLE KNOW IX LIKE CORN1	MARY VEG
40: JOHN IX *CORN *JOHN *IX	JOHN IX
THINK MARY LOVE 43: JOHN *JOHN BUY HOUSE	JOHN MUS
T BUY HOUSE 50: *JOHN *SEE BUY CAR *HOMEWORK	FUTURE J
OHN BUY CAR SHOULD 54: JOHN *JOHN *MARY BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE 57: *IX *JOHN *IX *IX	JOHN DEC
IDE VISIT MARY	
67: JOHN FUTURE *MARY BUY HOUSE URE NOT BUY HOUSE	JOHN FUT
71: JOHN *JOHN VISIT MARY L VISIT MARY	JOHN WIL
74: JOHN *MARY VISIT MARY VISIT MARY	ЈОНИ ИОТ
77: *JOHN BLAME MARY	ANN BLAM
E MARY  84: *JOHN *WRITE *HOMEWORK *WRITE	IX-1P FI
ND SOMETHING-ONE BOOK 89: *SOMETHING-ONE IX *THROW *GIVE IX *WRITE COAT	JOHN IX
GIVE MAN IX NEW COAT  90: JOHN *GIVE1 IX SOMETHING-ONE WOMAN *BORROW	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK 92: JOHN GIVE IX *IX WOMAN BOOK	
E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
100: POSS *WRITE CAR BREAK-DOWN CAR BREAK-DOWN	POSS NEW
105: JOHN *POSS 107: JOHN *JOHN FRIEND *MARY *MARY	JOHN LEG JOHN POS
S FRIEND HAVE CANDY	
108: *TOMORROW *HOMEWORK RIVE	WOMAN AR
113: *JOHN CAR *MARY *JOHN *BUY1 LUE SUE BUY	IX CAR B
119: *JOHN *BUY1 *JOHN CAR *JOHN IX CAR BLUE	SUE BUY

122: JOHN *BOOK BOOK	JOHN REA
D BOOK	
139: JOHN *BUY1 WHAT YESTERDAY *BORROW	JOHN BUY
WHAT YESTERDAY BOOK	
142: JOHN BUY YESTERDAY WHAT *WRITE	JOHN BUY
YESTERDAY WHAT BOOK	
158: LOVE JOHN *MARY	LOVE JOH
N WHO	
167: JOHN *GIVE2 *VISIT LOVE MARY	JOHN IX
SAY LOVE MARY	
171: JOHN *JOHN BLAME	JOHN MAR
Y BLAME	
174: *CAR GROUP GIVE1 *MARY TOY	PEOPLE G
ROUP GIVE1 JANA TOY	
181: *MARY *WHAT	JOHN ARR
IVE	
184: *IX BOY *GIVE1 TEACHER *YESTERDAY	ALL BOY
GIVE TEACHER APPLE	
189: JOHN *GIVE1 *VISIT *WHAT	JOHN GIV
E GIRL BOX	
193: JOHN *YESTERDAY *GO BOX	JOHN GIV
E GIRL BOX	
199: *JOHN *ARRIVE *MARY	LIKE CHO
COLATE WHO	
201: JOHN *GIVE1 *LOVE *LIKE BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	

In [97]: # run a test for a specific combination of features/selectors
 recognize\_and\_display\_result(features\_norm\_polar\_coords+features\_delta\_norm\_ha
 nd\_pos, selector\_sets[2] )

\*\*\*\* WER = 0.39325842696629215 Total correct: 108 out of 178

Total correct: 108 out of 178	
Video Recognized	Correct =========
=======================================	
2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK	
7: JOHN *CAR GO *WHAT	JOHN CAN
GO CAN	JOHN CAN
12: JOHN CAN *GO1 CAN GO CAN	JOHN CAN
21: JOHN *VIDEOTAPE WONT *WHO BUT *CAR *FUTURE *MARY	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	555
25: JOHN *IX *LOVE IX IX	JOHN LIK
E IX IX IX	
28: JOHN *WHO IX IX IX	JOHN LIK
E IX IX IX	
30: JOHN *MARY *MARY IX IX	JOHN LIK
E IX IX IX 36: MARY *JOHN *GIRL *GIVE *MARY *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1	MARY VEG
40: JOHN *GIVE *CORN MARY *MARY	JOHN IX
THINK MARY LOVE	501111 271
43: JOHN *POSS BUY HOUSE	JOHN MUS
T BUY HOUSE	
50: *JOHN JOHN BUY CAR *MARY	FUTURE J
OHN BUY CAR SHOULD	
54: JOHN *FUTURE *FUTURE BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	JOHN DEC
57: *MARY *JOHN VISIT MARY  IDE VISIT MARY	JOHN DEC
67: JOHN FUTURE NOT BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	301111 1 0 1
71: JOHN *FUTURE VISIT MARY	JOHN WIL
L VISIT MARY	
74: JOHN *MARY *MARY MARY	JOHN NOT
VISIT MARY	
77: *JOHN BLAME MARY	ANN BLAM
E MARY	TV 45 FT
84: *JOHN *BUY *HOMEWORK BOOK ND SOMETHING-ONE BOOK	IX-1P FI
89: JOHN *JOHN *WOMAN *THROW IX *BUY COAT	JOHN IX
GIVE MAN IX NEW COAT	JOHN IX
90: JOHN *IX IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
92: JOHN GIVE *WOMAN *WOMAN WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
100: POSS NEW CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	
105: JOHN *JOHN	JOHN LEG
107: JOHN *IX FRIEND *MARY *JOHN S FRIEND HAVE CANDY	JOHN POS
108: *JOHN *BOOK	WOMAN AR
RIVE	MONAN AIL
113: IX CAR *JOHN *JOHN *BUY1	IX CAR B
LUE SUE BUY	- · · -
119: *JOHN *BUY1 IX CAR *JANA	SUE BUY

TX CAR BILIF	
122: JOHN *GIVE1 BOOK	JOHN REA
D BOOK	
139: JOHN *BUY1 WHAT YESTERDAY BOOK	JOHN BUY
WHAT YESTERDAY BOOK	
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	
158: LOVE JOHN WHO	LOVE JOH
N WHO	
167: JOHN IX *IX LOVE MARY	JOHN IX
SAY LOVE MARY	
171: JOHN *JOHN BLAME	JOHN MAR
Y BLAME	
174: *GIVE1 GROUP GIVE1 *JOHN TOY	PEOPLE G
ROUP GIVE1 JANA TOY	
181: *SUE ARRIVE	JOHN ARR
IVE	
184: ALL BOY *GIVE1 TEACHER APPLE	ALL BOY
GIVE TEACHER APPLE	
189: JOHN *IX GIRL *CAR	JOHN GIV
E GIRL BOX	JOHN CTV
193: JOHN *IX GIRL BOX	JOHN GIV
E GIRL BOX	LTKE CHO
199: *JOHN *ARRIVE WHO COLATE WHO	LIKE CHO
201: JOHN *FUTURE MARY *JOHN BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	JOHN IEL
F LIMINI TV-TL DOI 11003F	

**Question 3:** Summarize the error results from three combinations of features and model selectors. What was the "best" combination and why? What additional information might we use to improve our WER? For more insight on improving WER, take a look at the introduction to Part 4.

**Answer 3:** The best combination from my original feature sets seems to have come from the combination of normalized polar coordinates with their deltas(features\_delta\_norm\_hand\_pos), and the DIC selector, with a WER = 0.4044, and Total correct: 106 out of 178. This can be attributed to several factors:

- The selector policy not overfitting the data, as opposed to what we anticipated w ith the last question. This may change as more data is used.
- The normalized polar coordinates/w deltas seem to better indicate hand position c orrectly.

The worst combination observed was using distance between hands, and the rate of change of that distance (features\_hand\_dist) with SelectorBIC, with a WER = 0.9213, and Total correct: 14 out of 178. The data set simply did not have enough features to be of use!

After observing the scores, I suspected that the hand distance should still be able to add value, so I combined the two data sets(features\_delta\_norm\_hand\_pos and features\_hand\_dist) and again used SelectorBIC to achieve the highest score observed in these tests: WER = 0.3932, and Total correct: 108 out of 178. This validates the idea that normalized data/polar coordinates/hand-distance features are the most valuable, and the original data needs to be greatly transformed to be most useful.

We can anticipate two methods to improve the score:

- Add more features: one method, mentioned in [Speech Recognition Techniques for a Sign Language Recognition System, Philippe Dreuw et al](https://www-i6.informatik.rwth-aachen.de/publications/download/154/Dreuw--2007.pdf), is to use PCA on each im age frame, to assist in capturing more information about hand orientation. Other tactics to be tried include using different combinations of the tested feature sets
- Improve our guess. This can be done in various ways, with the first and most obvious being to use a words probability of appearing in the same phrase as a modifier on probability, and calculating the guess based in that information, as outlined below!
- Improve our probabilities: First, we can optimize the hyperparameters of the mode l using a gridsearch or similar. Also, we can use ensemble methods, such as stacking to combine multiple models, for an improved probability set. This would require a bit or rework of the base\_model method, to convert everything over to a format that works for scikit learn and build a proper pipeline that can be returned as a mode l.

## **Recognizer Unit Tests**

Run the following unit tests as a sanity check on the defined recognizer. The test simply looks for some valid values but is not exhaustive. However, the project should not be submitted if these tests don't pass.

# PART 4: (OPTIONAL) Improve the WER with Language Models

We've squeezed just about as much as we can out of the model and still only get about 50% of the words right! Surely we can do better than that. Probability to the rescue again in the form of <a href="statistical language models">statistical language models</a> (SLM) (<a href="https://en.wikipedia.org/wiki/Language\_model">https://en.wikipedia.org/wiki/Language\_model</a>). The basic idea is that each word has some probability of occurrence within the set, and some probability that it is adjacent to specific other words. We can use that additional information to make better choices.

### Additional reading and resources

- Introduction to N-grams (Stanford Jurafsky slides)
   (https://web.stanford.edu/class/cs124/lec/languagemodeling.pdf)
- Speech Recognition Techniques for a Sign Language Recognition System, Philippe Dreuw et al (https://www-i6.informatik.rwth-aachen.de/publications/download/154/Dreuw--2007.pdf) see the improved results of applying LM on this data!
- SLM data for this ASL dataset (ftp://wasserstoff.informatik.rwth-aachen.de/pub/rwth-boston-104/lm/)

#### Optional challenge

The recognizer you implemented in Part 3 is equivalent to a "0-gram" SLM. Improve the WER with the SLM data provided with the data set in the link above using "1-gram", "2-gram", and/or "3-gram" statistics. The probabilities data you've already calculated will be useful and can be turned into a pandas DataFrame if desired (see next cell).

Good luck! Share your results with the class!

Out[93]:

	ALL	ANN	APPLE	ARRIVE	BILL	BLAME	BL
0	-2067.010836	-767.519589	-1539.325400	-83.791391	-1045.751728	-337.658776	-22
1	-7456.930610	-4643.414672	-3527.246300	158.675871	-6698.850106	-139.137972	-39
2	-10634.334063	-5419.519485	-5415.645160	193.809785	-9780.359478	-330.496706	-54
3	-1266.006788	-2052.018577	-886.241616	-51.800291	-1655.268607	-351.466072	-80
4	-2259.790386	-2052.046270	-760.550551	31.038891	-3682.778663	-23.609359	-14

5 rows × 112 columns

EOF - Submited for review 7-13-2017