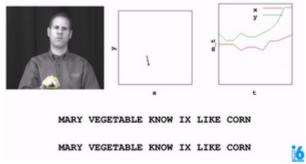
Artificial Intelligence Engineer Nanodegree - Probabilistic Models

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 https://en.wikipedia.org/wiki/Hidden_Markov_model) to analyze a series of measurements taken from videos of American Sign Language (ASL) collected for research (see the https://www-i6.informatik.rwth-aachen.de/~dreuw/database-rwth-boston-104.php)). 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 hmmlearn.readthedocs.io/en/latest/) 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. ⁻

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> (https://en.wikipedia.org/wiki/Standard_score) 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 2π discontinuity to 12 o'clock instead of 3 o'clock; in other words, the normal break in radians value from 0 to 2π 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 = \begin{bmatrix} 0.9894402 & -0.16006052 & -1.31412901 & -1.55560526 & 0.11903554 & -0.02124 \end{bmatrix}
        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]
```

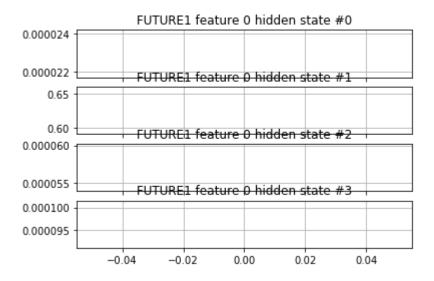
logL = 286.6984478044842

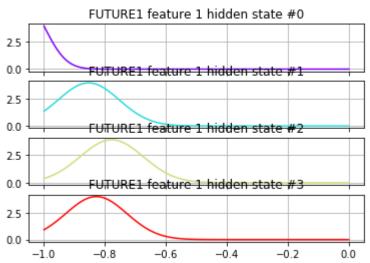
Visualize the hidden states

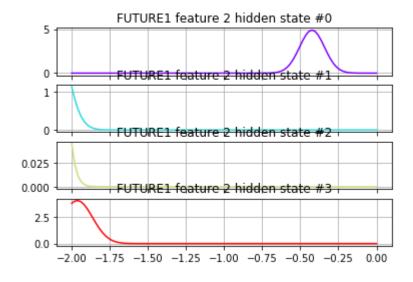
We can plot the means and variances for each state and feature. Try varying the number of states trained for the HMM model and examine the variances. Are there some models that are "better" than others? How can you tell? We would like to hear what you think in the classroom online.

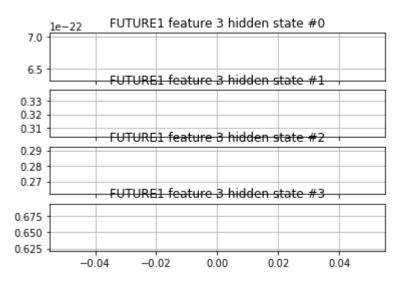
In [31]: %matplotlib inline

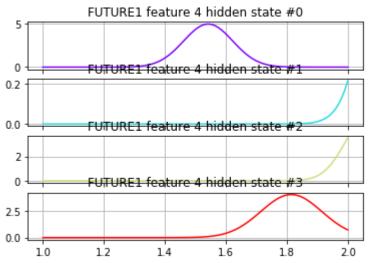
```
In [32]:
         import math
         from matplotlib import (cm, pyplot as plt, mlab)
         def visualize(word, model):
              """ visualize the input model for a particular word """
             variance=np.array([np.diag(model.covars_[i]) for i in range(model.n_compon
         ents)])
             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)
```



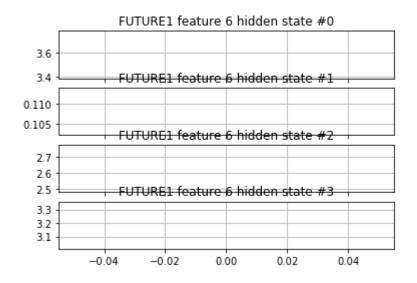


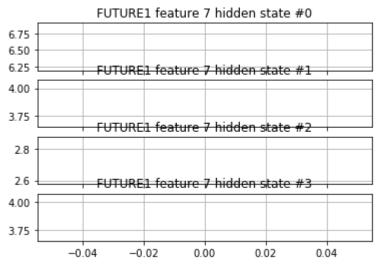


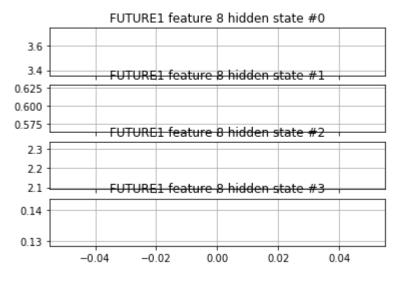


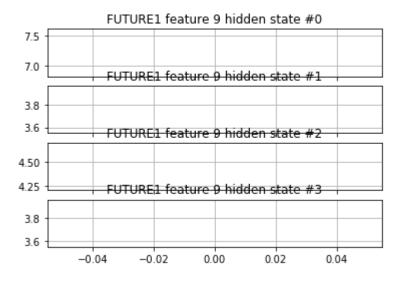


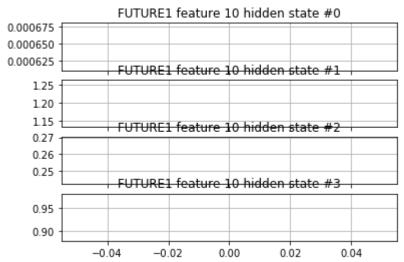


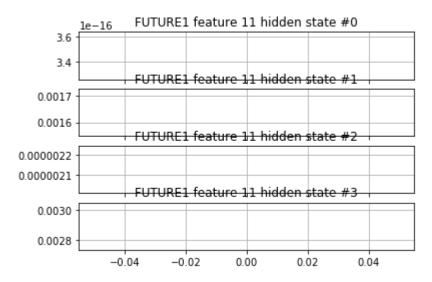


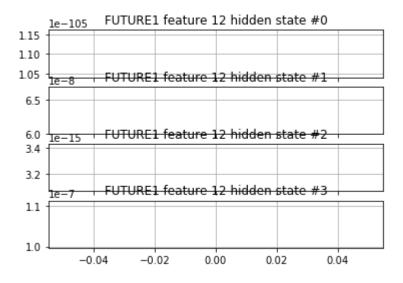


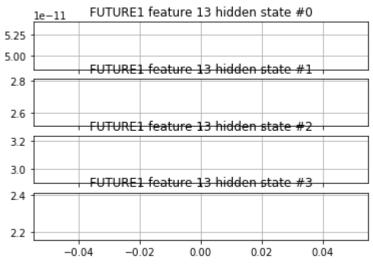


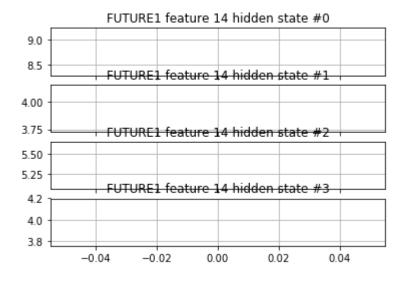


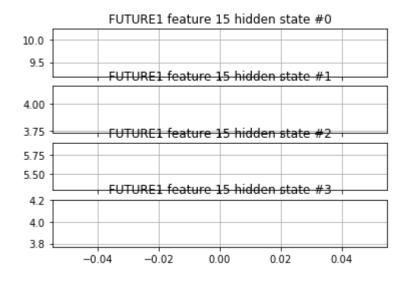


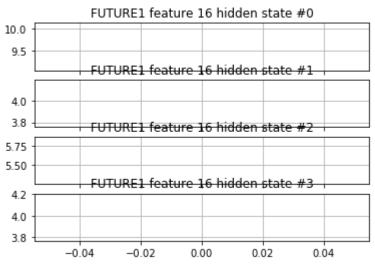


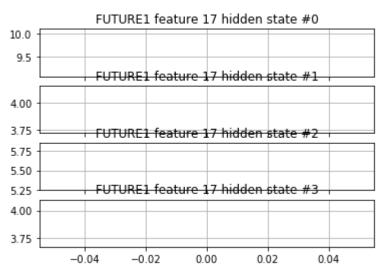












ModelSelector class

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 scikit-learn.org/stable/modules/generated/sklearn.model_selection.KFold.html) 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> (https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.58.6208&rep=rep1&type=pdf) (also found https://pdfs.semanticscholar.org/ed3d/7c4a5f607201f3848d4c02dd9ba17c791fc2.pdf)). 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 [111]: | # 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 failed for FISH

Training complete for BOOK with 6 states with time 2.81417334053549 seconds Training complete for VEGETABLE with 2 states with time 1.1776731134450529 seconds

Training complete for FUTURE with 2 states with time 2.5726160319172777 seconds

Training complete for JOHN with 12 states with time 28.304941846523434 second s

```
In [112]: # 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 7 states with time 0.4071681245986838 seconds Training complete for BOOK with 4 states with time 2.8164064593438525 seconds Training complete for VEGETABLE with 2 states with time 1.227136008325033 seconds

Training complete for FUTURE with 2 states with time 2.3431619242182933 secon ds

Training complete for JOHN with 6 states with time 43.67166417956469 seconds

```
In [113]: # 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 5 states with time 0.27201277599669993 second
          Training complete for BOOK with 8 states with time 1.4624717554543167 seconds
          Training complete for VEGETABLE with 9 states with time 0.5155715345754288 se
          Training complete for FUTURE with 9 states with time 1.5727507313131355 secon
          Training complete for JOHN with 13 states with time 15.105401587614324 second
```

```
In [114]: # 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 BOOK with 4 states with time 1.3124092013167683 seconds
Training complete for VEGETABLE with 3 states with time 0.5337541926128324 se
conds
Training complete for FUTURE with 6 states with time 1.2687507228401955 secon
ds
Training complete for JOHN with 8 states with time 25.431928486621473 seconds

Training complete for FISH with 3 states with time 0.2737800887261983 seconds

```
In [115]: # 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 0.626596999092726 seconds Training complete for BOOK with 15 states with time 4.045490319986129 seconds Training complete for VEGETABLE with 15 states with time 2.331507956434507 se conds
Training complete for FUTURE with 15 states with time 3.1904670896183234 seconds
Training complete for JOHN with 15 states with time 16.925838098366512 second

```
In [116]: # 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 2.4782326449349057 seconds Training complete for BOOK with 15 states with time 3.064980831783032 seconds Training complete for VEGETABLE with 7 states with time 2.3212852580763865 se conds

Training complete for FUTURE with 15 states with time 3.179895653796848 seconds

Training complete for JOHN with 15 states with time 29.18917686669738 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 DIC selector is overfitting, as they have tended to select models with more states. The CV selector is designed to overcome this and seems to use less states than the other selectors.

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 [118]: # 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

```
In [119]: test_set = asl.build_test(features_norm+features_custom)
    print("Number of test set items: {}".format(test_set.num_items))
    print("Number of test set sentences:
    {}".format(len(test_set.sentences_index)))
Number of test set items: 178
Number of test set sentences: 40
```

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 [120]: # TODO implement the recognize method in my_recognizer
from my_recognizer import recognize
from asl_utils import show_errors

```
In [121]: # 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 = 0.449438202247191 Total correct: 98 out of 178

Total correct: 98 out of 178 Video Recognized	Correct
=======================================	
2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK 7: JOHN *CAR GO CAN	JOHN CAN
GO CAN	JUNIN CAN
12: JOHN CAN *GO1 CAN	JOHN CAN
GO CAN	
21: JOHN *NEW *VISIT *JOHN *CAR *CAR *FUTURE *FUTURE	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN 25: JOHN *IX *LOVE *MARY IX	JOHN LIK
E IX IX IX	JOHN LIK
28: *ANN LIKE *ANN IX IX	JOHN LIK
E IX IX IX	
30: *IX *MARY *MARY IX IX	JOHN LIK
E IX IX IX	MARY VEC
36: MARY *JOHN *GIRL *VISIT *JOHN *MARY ETABLE KNOW IX LIKE CORN1	MARY VEG
40: JOHN IX *JOHN *JOHN *MARY	JOHN IX
THINK MARY LOVE	
43: JOHN *JOHN BUY HOUSE	JOHN MUS
T BUY HOUSE	FUTURE 3
50: *JOHN *SEE BUY CAR SHOULD OHN BUY CAR SHOULD	FUTURE J
54: JOHN SHOULD *FUTURE BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	
57: *IX *JOHN *IX *IX	JOHN DEC
IDE VISIT MARY	
67: JOHN FUTURE NOT BUY HOUSE URE NOT BUY HOUSE	JOHN FUT
71: JOHN *FUTURE VISIT MARY	JOHN WIL
L VISIT MARY	JOHN WIL
74: *IX *MARY *MARY MARY	JOHN NOT
VISIT MARY	
77: *JOHN BLAME MARY	ANN BLAM
E MARY 84: *JOHN *NEW *HOMEWORK BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	17 11 11
89: JOHN *POSS *MAN MAN IX NEW COAT	JOHN IX
GIVE MAN IX NEW COAT	
90: JOHN *GIVE1 IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *MAN IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
100: POSS NEW CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	
105: JOHN *SEE	JOHN LEG
107: *MARY *IX FRIEND *IX *JOHN	JOHN POS
S FRIEND HAVE CANDY 108: *MARY *HOMEWORK	WOMAN AR
RIVE	7.0.0.00
113: IX CAR *JOHN *JOHN *BUY1	IX CAR B
LUE SUE BUY	
119: *MARY *BUY1 IX CAR *IX	SUE BUY

```
IX CAR BLUE
            122: JOHN *GIVE1 BOOK
                                                                                 JOHN REA
            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 *VISIT LOVE MARY
                                                                                 JOHN IX
           SAY LOVE MARY
            171: *MARY *JOHN BLAME
                                                                                 JOHN MAR
          Y BLAME
            174: *CAR GROUP GIVE1 *JOHN TOY
                                                                                 PEOPLE G
          ROUP GIVE1 JANA TOY
            181: JOHN *VIDEOTAPE
                                                                                 JOHN ARR
          IVE
            184: ALL BOY *GIVE1 TEACHER APPLE
                                                                                 ALL BOY
           GIVE TEACHER APPLE
            189: JOHN *JOHN *PREFER *CAN
                                                                                 JOHN GIV
          E GIRL BOX
            193: JOHN *IX *YESTERDAY BOX
                                                                                 JOHN GIV
          E GIRL BOX
            199: *JOHN CHOCOLATE *JOHN
                                                                                 LIKE CHO
          COLATE WHO
            201: JOHN *GIVE1 *WOMAN *WOMAN BUY HOUSE
                                                                                 JOHN TEL
          L MARY IX-1P BUY HOUSE
          #set up a function of the above for the above, for better re-use!
In [122]:
          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 [123]:
          # 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 [124]: 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	SUE BUY
IX CAR BLUE 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 Y BLAME	JOHN MAR
174: *CAN *GIVE3 GIVE1 *APPLE *WHAT	PEOPLE G
ROUP GIVE1 JANA TOY 181: *BLAME ARRIVE	JOHN ARR
IVE	ALL DOV
184: *GIVE1 BOY *GIVE1 TEACHER APPLE GIVE TEACHER APPLE	ALL BOY
189: *JANA *SOMETHING-ONE *YESTERDAY *WHAT E GIRL BOX	JOHN GIV
193: JOHN *SOMETHING-ONE *YESTERDAY BOX	JOHN GIV
E GIRL BOX 199: *LOVE CHOCOLATE WHO	LIKE CHO
COLATE WHO 201: JOHN *GIVE *GIVE *LOVE *ARRIVE HOUSE	JOHN TEI
L MARY IX-1P BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my<="" td=""><td></td></class>	
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'=""> **** WER = 0.550561797752809 Total correct: 80 out of 178</class>	/_model_se
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L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'=""> **** WER = 0.550561797752809 Total correct: 80 out of 178 Video Recognized</class>	/_model_se Correct ====== JOHN WRI
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'=""> **** WER = 0.550561797752809 Total correct: 80 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 = 0.550561797752809 Total correct: 80 out of 178 Video Recognized ====================================</class>	/_model_se Correct ====== JOHN WRI
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'=""> **** WER = 0.550561797752809 Total correct: 80 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 = 0.550561797752809 Total correct: 80 out of 178 Video Recognized</class>	Correct JOHN WRI JOHN CAN JOHN FIS
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'=""> **** WER = 0.550561797752809 Total correct: 80 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 = 0.550561797752809 Total correct: 80 out of 178 Video Recognized ====================================</class>	Correct JOHN WRI JOHN CAN JOHN FIS
L MARY IX-1P BUY HOUSErunning: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my="" lectors.selectorbic'=""> **** WER = 0.550561797752809 Total correct: 80 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 = 0.550561797752809 Total correct: 80 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 = 0.550561797752809 Total correct: 80 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 = 0.550561797752809 Total correct: 80 out of 178 Video Recognized</class>	Correct JOHN WRI JOHN CAN JOHN FIS JOHN LIK JOHN LIK MARY VEG

T BUY HOUSE	
50: *JOHN *SEE BUY CAR *NEW	FUTURE J
OHN BUY CAR SHOULD	
54: JOHN SHOULD NOT BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	JOHN DEC
57: *MARY *VISIT VISIT MARY IDE VISIT MARY	JOHN DEC
67: *SHOULD *JOHN *WHO BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN *FUTURE VISIT MARY	JOHN WIL
L VISIT MARY	
74: *IX *VISIT VISIT MARY	JOHN NOT
VISIT MARY 77: *JOHN BLAME *LOVE	ANN BLAM
E MARY	ANN DEAM
84: *JOHN *ARRIVE *GIVE1 BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	
89: *MARY *POSS *IX *IX IX *ARRIVE *BOOK	JOHN IX
GIVE MAN IX NEW COAT	JOHN CTV
90: JOHN *SOMETHING-ONE IX *IX *VISIT *ARRIVE E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
92: JOHN *SHOULD IX *IX *IX BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
100: *IX NEW CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	
105: JOHN *FRANK	JOHN LEG
107: JOHN *GO *ARRIVE HAVE *JOHN S FRIEND HAVE CANDY	JOHN POS
108: *WHO *LOVE	LIOMANI AD
100. WHO LOVE	WOMAN AR
RIVE	WOMAN AK
RIVE 113: IX CAR *CAR *MARY *BOX	IX CAR B
RIVE 113: IX CAR *CAR *MARY *BOX LUE SUE BUY	IX CAR B
RIVE 113: IX CAR *CAR *MARY *BOX LUE SUE BUY 119: *VISIT *BUY1 IX *BOX *GO	-
RIVE 113: IX CAR *CAR *MARY *BOX LUE SUE BUY 119: *VISIT *BUY1 IX *BOX *GO IX CAR BLUE	IX CAR B
RIVE 113: IX CAR *CAR *MARY *BOX LUE SUE BUY 119: *VISIT *BUY1 IX *BOX *GO	IX CAR B
RIVE 113: IX CAR *CAR *MARY *BOX LUE SUE BUY 119: *VISIT *BUY1 IX *BOX *GO IX CAR BLUE 122: JOHN *GIVE1 BOOK	IX CAR B
RIVE 113: IX CAR *CAR *MARY *BOX LUE SUE BUY 119: *VISIT *BUY1 IX *BOX *GO IX CAR BLUE 122: JOHN *GIVE1 BOOK D BOOK 139: JOHN *BUY1 WHAT *GIVE1 BOOK WHAT YESTERDAY BOOK	IX CAR B SUE BUY JOHN REA JOHN BUY
RIVE 113: IX CAR *CAR *MARY *BOX LUE SUE BUY 119: *VISIT *BUY1 IX *BOX *GO IX CAR BLUE 122: JOHN *GIVE1 BOOK D BOOK 139: JOHN *BUY1 WHAT *GIVE1 BOOK WHAT YESTERDAY BOOK 142: JOHN *STUDENT YESTERDAY WHAT BOOK	IX CAR B SUE BUY JOHN REA
RIVE 113: IX CAR *CAR *MARY *BOX LUE SUE BUY 119: *VISIT *BUY1 IX *BOX *GO IX CAR BLUE 122: JOHN *GIVE1 BOOK D BOOK 139: JOHN *BUY1 WHAT *GIVE1 BOOK WHAT YESTERDAY BOOK 142: JOHN *STUDENT YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY
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RIVE 113: IX CAR *CAR *MARY *BOX LUE SUE BUY 119: *VISIT *BUY1 IX *BOX *GO IX CAR BLUE 122: JOHN *GIVE1 BOOK D BOOK 139: JOHN *BUY1 WHAT *GIVE1 BOOK WHAT YESTERDAY BOOK 142: JOHN *STUDENT YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY
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RIVE 113: IX CAR *CAR *MARY *BOX LUE SUE BUY 119: *VISIT *BUY1 IX *BOX *GO IX CAR BLUE 122: JOHN *GIVE1 BOOK D BOOK 139: JOHN *BUY1 WHAT *GIVE1 BOOK WHAT YESTERDAY BOOK 142: JOHN *STUDENT YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK 158: LOVE JOHN WHO N WHO 167: JOHN *MARY *VISIT LOVE MARY SAY LOVE MARY 171: JOHN MARY BLAME Y BLAME	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX JOHN MAR
RIVE 113: IX CAR *CAR *MARY *BOX LUE SUE BUY 119: *VISIT *BUY1 IX *BOX *GO IX CAR BLUE 122: JOHN *GIVE1 BOOK D BOOK 139: JOHN *BUY1 WHAT *GIVE1 BOOK WHAT YESTERDAY BOOK 142: JOHN *STUDENT YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK 158: LOVE JOHN WHO N WHO 167: JOHN *MARY *VISIT LOVE MARY SAY LOVE MARY 171: JOHN MARY BLAME Y BLAME 174: *CAN *GIVE1 GIVE1 *YESTERDAY *WHAT	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX
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RIVE 113: IX CAR *CAR *MARY *BOX LUE SUE BUY 119: *VISIT *BUY1 IX *BOX *GO IX CAR BLUE 122: JOHN *GIVE1 BOOK D BOOK 139: JOHN *BUY1 WHAT *GIVE1 BOOK WHAT YESTERDAY BOOK 142: JOHN *STUDENT YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK 158: LOVE JOHN WHO N WHO 167: JOHN *MARY *VISIT LOVE MARY SAY LOVE MARY 171: JOHN MARY BLAME Y BLAME 174: *CAN *GIVE1 GIVE1 *YESTERDAY *WHAT	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX JOHN MAR
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RIVE 113: IX CAR *CAR *MARY *BOX LUE SUE BUY 119: *VISIT *BUY1 IX *BOX *GO IX CAR BLUE 122: JOHN *GIVE1 BOOK D BOOK 139: JOHN *BUY1 WHAT *GIVE1 BOOK WHAT YESTERDAY BOOK 142: JOHN *STUDENT YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK 158: LOVE JOHN WHO N WHO 167: JOHN *MARY *VISIT LOVE MARY SAY LOVE MARY 171: JOHN MARY BLAME Y BLAME 174: *CAN *GIVE1 GIVE1 *YESTERDAY *WHAT ROUP GIVE1 JANA TOY 181: JOHN *BOX IVE 184: *GIVE BOY *GIVE1 TEACHER APPLE GIVE TEACHER APPLE 189: JOHN *SOMETHING-ONE *VISIT BOX	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX JOHN MAR PEOPLE G JOHN ARR
RIVE 113: IX CAR *CAR *MARY *BOX LUE SUE BUY 119: *VISIT *BUY1 IX *BOX *GO IX CAR BLUE 122: JOHN *GIVE1 BOOK D BOOK 139: JOHN *BUY1 WHAT *GIVE1 BOOK WHAT YESTERDAY BOOK 142: JOHN *STUDENT YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK 158: LOVE JOHN WHO N WHO 167: JOHN *MARY *VISIT LOVE MARY SAY LOVE MARY 171: JOHN MARY BLAME Y BLAME 174: *CAN *GIVE1 GIVE1 *YESTERDAY *WHAT ROUP GIVE1 JANA TOY 181: JOHN *BOX IVE 184: *GIVE BOY *GIVE1 TEACHER APPLE GIVE TEACHER APPLE 189: JOHN *SOMETHING-ONE *VISIT BOX E GIRL BOX	IX CAR B SUE BUY JOHN REA JOHN BUY LOVE JOH JOHN IX JOHN MAR PEOPLE G JOHN ARR ALL BOY JOHN GIV
RIVE 113: IX CAR *CAR *MARY *BOX LUE SUE BUY 119: *VISIT *BUY1 IX *BOX *GO IX CAR BLUE 122: JOHN *GIVE1 BOOK D BOOK 139: JOHN *BUY1 WHAT *GIVE1 BOOK WHAT YESTERDAY BOOK 142: JOHN *STUDENT YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK 158: LOVE JOHN WHO N WHO 167: JOHN *MARY *VISIT LOVE MARY SAY LOVE MARY 171: JOHN MARY BLAME Y BLAME 174: *CAN *GIVE1 GIVE1 *YESTERDAY *WHAT ROUP GIVE1 JANA TOY 181: JOHN *BOX IVE 184: *GIVE BOY *GIVE1 TEACHER APPLE GIVE TEACHER APPLE 189: JOHN *SOMETHING-ONE *VISIT BOX	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX JOHN MAR PEOPLE G JOHN ARR ALL BOY
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COLATE WHO 201: JOHN *MARY *LOVE *JOHN BUY 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 FUTURE J

50: *JOHN *FUTURE *GIVE1 CAR *JOHN

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 CAR BREAK-DOWN

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

S FRIEND HAVE CANDY	
108: *IX ARRIVE	WOMAN AR
RIVE 113: IX CAR *IX *MARY *BOX	IX CAR B
LUE SUE BUY	IX CAN D
119: *VISIT *BUY1 IX *BOX *IX	SUE BUY
IX CAR BLUE	
122: JOHN *BUY BOOK D BOOK	JOHN REA
139: JOHN *BUY1 WHAT *MARY 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	LOVE JOH
167: JOHN *MARY *GO LOVE MARY	JOHN IX
SAY LOVE MARY	
171: JOHN MARY BLAME	JOHN MAR
Y BLAME 174: *CAR *GIVE1 GIVE1 *YESTERDAY *WHAT	PEOPLE G
ROUP GIVE1 JANA TOY	FLOFEL G
181: JOHN ARRIVE	JOHN ARR
IVE	
184: *IX BOY *GIVE1 TEACHER *YESTERDAY	ALL BOY
GIVE TEACHER APPLE 189: JOHN *SOMETHING-ONE *VISIT BOX	JOHN GIV
E GIRL BOX	JOHN GIV
193: JOHN *SOMETHING-ONE *VISIT BOX	JOHN GIV
E GIRL BOX	
199: *JOHN *ARRIVE *GO COLATE WHO	LIKE CHO
201: JOHN *MARY *LOVE *JOHN *GIVE1 HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	
running: ['grnd-rx', 'grnd-ry', 'grnd-lx', 'grnd-ly'] <class 'my<="" td=""><td>_model_se</td></class>	_model_se
lectors.SelectorCV'>	
**** WER = 0.5898876404494382	
Total correct: 73 out of 178	
Video Recognized	Correct
	=======
2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK	
7: JOHN *WHAT GO *HAVE	JOHN CAN
GO CAN	701111 0441
12: *LAST-WEEK *TEACHER *CAN CAN GO CAN	JOHN CAN
21: JOHN *VIDEOTAPE *HOMEWORK *FUTURE *CAR *CAR *VISIT *TOMORROW	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	
25: JOHN *IX *LOVE IX IX	JOHN LIK
E IX IX IX	JOHN LTV
28: JOHN *TELL IX IX *LOVE E IX IX IX	JOHN LIK
30: JOHN *IX *SHOOT *SHOOT	JOHN LIK
E IX IX IX	
36: MARY VEGETABLE *GIVE *SHOOT *MARY *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1	

40: JOHN *GIVE *APPLE *JOHN *SHOOT THINK MARY LOVE	JOHN IX
43: JOHN *SHOULD BUY HOUSE T BUY HOUSE	JOHN MUS
50: *JOHN *SEE BUY CAR *SOMETHING-ONE	FUTURE J
OHN BUY CAR SHOULD 54: JOHN SHOULD *GIVE1 BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE 57: *IX *VEGETABLE *MARY *IX	JOHN DEC
IDE VISIT MARY	JOHN DEC
67: JOHN *JOHN NOT *ARRIVE HOUSE URE NOT BUY HOUSE	JOHN FUT
71: JOHN *FINISH *GO MARY	JOHN WIL
L VISIT MARY	70.00 007
74: *IX *JANA *SHOOT *SHOOT VISIT MARY	JOHN NOT
77: *JOHN BLAME *LOVE	ANN BLAM
E MARY	
84: *LOVE *ARRIVE *GO *WRITE	IX-1P FI
ND SOMETHING-ONE BOOK	JOHN IX
89: *FRANK *POSS GIVE *IX IX *BUY *BOOK GIVE MAN TX NEW COAT	JOHN IX
90: JOHN *SOMETHING-ONE *SOMETHING-ONE SOMETHING-ONE WOMAN *BORRO	W JOHN G
IVE IX SOMETHING-ONE WOMAN BOOK	
92: JOHN GIVE IX *IX *MARY BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	DOCC NELL
100: POSS NEW CAR BREAK-DOWN CAR BREAK-DOWN	POSS NEW
105: JOHN *FRANK	JOHN LEG
107: JOHN *HAVE FRIEND *GO *WHO	JOHN POS
S FRIEND HAVE CANDY	
108: *FRANK *LOVE	WOMAN AR
RIVE	
113: *HAVE CAR *GIVE *MARY *HAVE	IX CAR B
LUE SUE BUY 119: *VEGETABLE *LOVE *HAVE *WHAT *GIVE	SUE BUY
IX CAR BLUE	JUL DUT
122: JOHN *HOUSE BOOK	JOHN REA
D BOOK	
139: JOHN *BUY1 *CAN YESTERDAY *BORROW	JOHN BUY
WHAT YESTERDAY BOOK	70111 8187
142: JOHN *NEW *CHICAGO *TEACHER BOOK YESTERDAY WHAT BOOK	JOHN BUY
158: LOVE JOHN WHO	LOVE JOH
N WHO	
167: JOHN *MARY *JANA *WOMAN *LOVE	JOHN IX
SAY LOVE MARY	
171: JOHN *JOHN BLAME	JOHN MAR
Y BLAME 174: *WHAT GROUP GIVE1 *APPLE TOY	PEOPLE G
ROUP GIVE1 JANA TOY	T LOT LL G
181: *HAVE *BOX	JOHN ARR
IVE	
184: *SOMETHING-ONE *GO *HOUSE TEACHER APPLE	ALL BOY
GIVE TEACHER APPLE 189: JOHN GIVE *YESTERDAY *CAN	
ACOL SOUN CLARE LEGIENDAI CAN	JOHN GTV
E GIRL BOX	JOHN GIV

193: JOHN *SOMETHING-ONE *GIVE1 BOX	JOHN GIV
E GIRL BOX 199: *LOVE CHOCOLATE *TELL COLATE WHO	LIKE CHO
201: JOHN *SHOULD *WOMAN *FRANK *ARRIVE HOUSE	JOHN TEL
<pre>L MARY IX-1P BUY HOUSErunning: ['norm-rx', 'norm-ry', 'norm-lx', 'norm-ly'] <class '="" lectors.selectorconstant'=""></class></pre>	my_model_se
**** WER = 0.6235955056179775 Total correct: 67 out of 178 Video Recognized	Correct
2: *MARY WRITE *ARRIVE	JOHN WRI
TE HOMEWORK 7: JOHN *NEW *JOHN CAN GO CAN	JOHN CAN
12: *SHOULD *HAVE *GO1 CAN GO CAN	JOHN CAN
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 E IX IX	JOHN LIK
28: *ANN LIKE *ANN *LIKE *ANN E IX IX	JOHN LIK
30: *SHOOT LIKE *LOVE *LIKE *MARY E IX IX	JOHN LIK
36: *LEAVE *NOT *YESTERDAY *VISIT LIKE *JOHN ETABLE KNOW IX LIKE CORN1	MARY VEG
40: JOHN *LEAVE *FUTURE1 *VEGETABLE LOVE THINK MARY LOVE	JOHN IX
43: JOHN *SHOULD BUY HOUSE T BUY HOUSE	JOHN MUS
50: *FRANK *SEE *ARRIVE CAR *CAR OHN BUY CAR SHOULD	FUTURE J
54: JOHN SHOULD *FUTURE *STUDENT HOUSE ULD NOT BUY HOUSE	JOHN SHO
57: *MARY *MARY *MARY MARY IDE VISIT MARY	JOHN DEC
67: *IX-1P FUTURE *JOHN *ARRIVE HOUSE URE NOT BUY HOUSE	JOHN FUT
71: JOHN WILL VISIT MARY	JOHN WIL
L VISIT MARY 74: *WOMAN *VISIT VISIT *FRANK	TON NHOC
VISIT MARY 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 GIV
E IX SOMETHING-ONE WOMAN BOOK 100: POSS NEW CAR BREAK-DOWN	POSS NEW

CAR BREAK-DOWN 105: *WHO *SEE	JOHN LEG
107: *TELL *IX *BOX *LIKE *JANA	JOHN POS
S FRIEND HAVE CANDY	
108: *LOVE *HOMEWORK	WOMAN AR
RIVE	
113: IX CAR *IX SUE *HAVE	IX CAR B
LUE SUE BUY	CUE DINA
119: *VEGETABLE *BUY1 IX CAR *GO IX CAR BLUE	SUE BUY
122: JOHN *HOUSE *COAT	JOHN REA
D BOOK	JOHN KLA
139: JOHN *BUY1 *CAR YESTERDAY BOOK	JOHN BUY
WHAT YESTERDAY BOOK	
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	
158: LOVE *MARY *CORN	LOVE JOH
N WHO	
167: JOHN *JOHN *SAY-1P LOVE MARY	JOHN IX
SAY LOVE MARY	JOHN MAD
171: *SHOOT *JOHN BLAME Y BLAME	JOHN MAR
174: *NEW *GIVE1 GIVE1 *WHO *CAR	PEOPLE G
ROUP GIVE1 JANA TOY	. 20. 22 0
181: JOHN *BOX	JOHN ARR
IVE	
184: *IX *IX *GIVE1 TEACHER APPLE	ALL BOY
GIVE TEACHER APPLE	
189: *JANA *SEE *PREFER *ARRIVE	JOHN GIV
E GIRL BOX	JOHN CTV
193: JOHN *SEE *YESTERDAY BOX E GIRL BOX	JOHN GIV
199: *JOHN CHOCOLATE *JOHN	LIKE CHO
COLATE WHO	LIKE CHO
201: JOHN *THINK *WOMAN *WOMAN *STUDENT HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	
running: ['norm-rx', 'norm-ry', 'norm-lx', 'norm-ly'] <class 'my<="" td=""><td>_model_se</td></class>	_model_se
<pre>lectors.SelectorBIC'></pre>	
hhhhh 1150 0 6400505505647070	
**** WER = 0.6123595505617978	
Total correct: 69 out of 178 Video Recognized	Correct
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2: JOHN WRITE *ARRIVE	JOHN WRI
TE HOMEWORK	
7: *MARY *NEW GO *WHAT	JOHN CAN
GO CAN	
12: *MARY *HAVE *GO1 CAN	JOHN CAN
GO CAN 21: *MARY *BOX *HAVE *GO *CAR *CAR *CHICKEN *WRITE	JOHN ETC
H WONT EAT BUT CAN EAT CHICKEN	JOHN FIS
25: JOHN LIKE *LOVE *LIKE IX	JOHN LIK
E IX IX IX	Lan
28: *ANN *ANN *ANN *ANN	JOHN LIK
E IX IX IX	
30: *IX-1P *IX *MARY IX IX	JOHN LIK

F TX TX TX	
36: MARY *MARY *YESTERDAY *SHOOT LIKE *IX	MARY VEG
ETABLE KNOW IX LIKE CORN1	TRACT VEG
40: *MARY *JOHN *FUTURE1 *VEGETABLE *MARY	JOHN IX
THINK MARY LOVE	
43: JOHN *FUTURE BUY HOUSE	JOHN MUS
T BUY HOUSE	
50: *POSS *SEE *WRITE CAR *CAR	FUTURE J
OHN BUY CAR SHOULD	701111 6110
54: JOHN *FUTURE *FUTURE *STUDENT HOUSE ULD NOT BUY HOUSE	JOHN SHO
57: *IX *IX MARY	JOHN DEC
IDE VISIT MARY	JOHN DEC
67: *MARY *IX *JOHN *ARRIVE HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN WILL VISIT MARY	JOHN WIL
L VISIT MARY	
74: *IX *BILL VISIT MARY	JOHN NOT
VISIT MARY	
77: *JOHN BLAME MARY	ANN BLAM
E MARY	TV 1D FT
84: *JOHN *HAVE *VISIT BOOK ND SOMETHING-ONE BOOK	IX-1P FI
89: *FUTURE *THROW *IX *IX IX *ARRIVE *BREAK-DOWN	JOHN IX
GIVE MAN IX NEW COAT	JOHN IX
90: *SELF *YESTERDAY IX *IX WOMAN *CHOCOLATE	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
92: JOHN *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 *FUTURE	JOHN LEG
107: *MARY POSS *BOX *MARY *TOY1 S FRIEND HAVE CANDY	JOHN POS
108: *IX *HOMEWORK	WOMAN AR
RIVE	MONAN AN
113: IX CAR *IX *JOHN *BOX	IX CAR B
LUE SUE BUY	
119: SUE *BUY1 IX CAR *FINISH	SUE BUY
IX CAR BLUE	
122: JOHN *GIVE1 BOOK	JOHN REA
D BOOK	
139: JOHN *BUY1 *CAR YESTERDAY BOOK	JOHN BUY
WHAT YESTERDAY BOOK 142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BIN
YESTERDAY WHAT BOOK	JOHN BUY
158: LOVE *IX WHO	LOVE JOH
N WHO	2012 30
167: *MARY IX *SAY-1P LOVE *IX	JOHN IX
SAY LOVE MARY	
171: *MARY *IX BLAME	JOHN MAR
Y BLAME	
174: *NEW *GIVE1 GIVE1 *VISIT *CAR	PEOPLE G
ROUP GIVE1 JANA TOY	JOHN ADD
181: JOHN *BOX IVE	JOHN ARR
184: *IX BOY *GIVE1 TEACHER APPLE	ALL BOY
10., 17 DOT GIVET TEACHER AT LE	ALL DOT

CTVE TEACHED ADDLE	
GIVE TEACHER APPLE 189: *JANA *MARY *PREFER *ARRIVE	JOHN GIV
E GIRL BOX	JOHN GIV
193: *IX *YESTERDAY *YESTERDAY BOX	JOHN GIV
E GIRL BOX	
199: *JOHN CHOCOLATE *JOHN	LIKE CHO
COLATE WHO 201: JOHN *GIVE1 *WOMAN *WOMAN *STUDENT HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	30
running: ['norm-rx', 'norm-ry', 'norm-lx', 'norm-ly'] <class 'm<="" td=""><td>y_model_se</td></class>	y_model_se
lectors.SelectorDIC'>	
**** WER = 0.5955056179775281	
Total correct: 72 out of 178	
Video Recognized	Correct
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2: JOHN WRITE *ARRIVE TE HOMEWORK	JOHN WRI
7: *MARY *CAR GO CAN	JOHN CAN
GO CAN	JOHN 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	70.00
25: JOHN LIKE IX *LIKE IX E IX IX IX	JOHN LIK
28: *ANN *ANN IX *MARY IX	JOHN LIK
E IX IX IX	JOHN LIK
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	JOHN TV
40: *MARY *JOHN *FUTURE1 *VEGETABLE *MARY THINK MARY LOVE	JOHN IX
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	JOHN DEC
67: *MARY *IX *JOHN *ARRIVE HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN *FUTURE VISIT MARY	JOHN WIL
L VISIT MARY	70.0.
74: *GO *VISIT VISIT MARY VISIT MARY	JOHN NOT
77: ANN BLAME MARY	ANN BLAM
E MARY	AIR BEAT
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	JOHN GIA
E 1/ SOMETHING ONE MOUNT DOOK	

92: JOHN *IX IX *IX *LOVE BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK 100: POSS NEW CAR BREAK-DOWN 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 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 D BOOK	JOHN REA
139: JOHN *BUY1 *CAR *JOHN 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	LOVE JOH
167: JOHN IX *SAY-1P LOVE *IX SAY LOVE MARY	JOHN IX
171: *MARY *JOHN BLAME	JOHN MAR
Y BLAME 174: *CAR *GIVE1 GIVE1 *YESTERDAY *CAR	PEOPLE G
ROUP GIVE1 JANA TOY	T LOT LL G
181: JOHN *BOX IVE	JOHN ARR
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 E GIRL BOX	JOHN GIV
199: *JOHN *ARRIVE *JOHN	LIKE CHO
COLATE WHO 201: JOHN *GIVE1 *IX *WOMAN *ARRIVE HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	
running: ['norm-rx', 'norm-ry', 'norm-lx', 'norm-ly'] <class 'my="" lectors.selectorcv'=""></class>	/_mode1_se
**** WER = 0.6797752808988764 Total correct: 57 out of 178	
Video Recognized	Correct
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2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK 7: JOHN *NEW *MARY *ARRIVE	JOHN CAN
GO CAN 12: *WHAT *WHAT *GO1 CAN	JOHN CAN
GO CAN	
21: *LIKE FISH *HAVE *IX-1P *VISIT *BLAME *FUTURE *HAVE H WONT EAT BUT CAN EAT CHICKEN	JOHN FIS
25: *ANN LIKE *ANN *LIKE *ANN	JOHN LIK
E IX IX IX	

28: *ANN *ANN *ANN *ANN	JOHN LIK
E IX IX IX	JOHN LIK
30: *IX-1P LIKE *SHOOT *LIKE *SHOOT E IX IX IX	JUNN LIK
36: *SHOOT *NOT *YESTERDAY *SHOOT *LEAVE *LIKE	MARY VEG
ETABLE KNOW IX LIKE CORN1	
40: JOHN *VISIT *SELF *NOT LOVE	JOHN IX
THINK MARY LOVE	
43: JOHN *JOHN BUY HOUSE	JOHN MUS
T BUY HOUSE	EUTURE 7
50: *POSS *FRANK *HAVE *HAVE *SOMETHING-ONE OHN BUY CAR SHOULD	FUTURE J
54: JOHN *JOHN *PREFER *WRITE HOUSE	JOHN SHO
ULD NOT BUY HOUSE	301114 3110
57: *SHOOT *WHO *MARY *SHOOT	JOHN DEC
IDE VISIT MARY	
67: *LIKE FUTURE *JOHN *LAST-WEEK HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN *PREFER *BLAME MARY	JOHN WIL
L VISIT MARY	JOHN NOT
74: JOHN *BILL VISIT *LOVE VISIT MARY	JOHN NOT
77: ANN *MARY *LOVE	ANN BLAM
E MARY	ANN BEAN
84: *JOHN *HOMEWORK *POSS *WRITE	IX-1P FI
ND SOMETHING-ONE BOOK	
89: *WHO *THROW *GO *MARY IX NEW COAT	JOHN IX
GIVE MAN IX NEW COAT	
90: *SELF *GIVE1 IX *FUTURE WOMAN *LOVE	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *GIVE1 IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	JOHN GIA
100: POSS NEW *HOUSE BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	
105: JOHN *POSS	JOHN LEG
107: *TELL *IX *BOX *LIKE *TOY1	JOHN POS
S FRIEND HAVE CANDY	
108: *LOVE *HOMEWORK	WOMAN AR
RIVE 113: *HIT CAR *IX *JOHN *BOX	IX CAR B
LUE SUE BUY	IX CAN B
119: *NOT *BUY1 *SOMETHING-ONE *PEOPLE *SUE	SUE BUY
IX CAR BLUE	
122: JOHN *HOUSE BOOK	JOHN REA
D BOOK	
139: JOHN *BUY1 *VIDEOTAPE YESTERDAY *LOVE	JOHN BUY
WHAT YESTERDAY BOOK	TOUR DUN
142: JOHN *ARRIVE *CHICAGO WHAT *COAT YESTERDAY WHAT BOOK	JOHN BUY
158: LOVE *MARY *CORN	LOVE JOH
N WHO	2012 30
167: *TELL *GIVE2 *VISIT LOVE MARY	JOHN IX
SAY LOVE MARY	
171: *JANA *JOHN BLAME	
	JOHN MAR
Y BLAME	
Y BLAME 174: *NEW GROUP GIVE1 *TELL TOY ROUP GIVE1 JANA TOY	JOHN MAR PEOPLE G

181: "YISIT "BOX JOHN ARR IVE 184: "IX BOY "GIVE1 TEACHER APPLE 184: "IX BOY "GIVE1 TEACHER APPLE 189: "TOY" "GIVE1 "NOT "ARRIVE 30HN GIV E GIRL BOX 199: JOHN "SEE "WHO BOX 199: JOHN CHOCOLATE "JOHN LIKE CHO COLATE WHO 201: JOHN "GIVE1 "WOMAN "WOMAN "WRITE HOUSE """, "polar-1r", "polar-lheta" cclass """, "my_model_selectors.SelectorConstant" > """, "model_selectors.SelectorConstant" > """, "model_selectors.SelectorConstant" > """, "model_selectors.SelectorConstant" > """, "JOHN "WRITE HOWEWORK JOHN WRITE HOWEWORK JOHN CAN GO CAN 21: "IX "HOMEWORK WONT "FUTURE "CAR "CAR "GO "TOMORROW JOHN CAN GO CAN 21: "IX "HOMEWORK WONT "FUTURE "CAR "CAR "GO "TOMORROW JOHN LIK E IX IX IX JOHN WHAT "WATH "WOTH LIK "CAR "CAR "GO "TOMORROW JOHN LIK E IX IX IX JOHN WHAT "WOTH "FUTURE "CAR "CAR "GO "TOMORROW JOHN LIK E IX IX IX "WHO "FUTURE "FUTURE IX JOHN LIK E IX IX IX "WHO "FUTURE "FUTURE "CAR "GO "TOMORROW JOHN LIK E IX IX IX "WHO "FUTURE "FUTURE IX JOHN LIK E IX IX IX "WHO "FUTURE "FUTURE IX JOHN LIK E IX IX IX "WHO "FUTURE "FUTURE IX JOHN LIK E IX IX IX "WHO "FUTURE "FUTURE IX JOHN LIK E IX IX IX "WHO "FUTURE "FUTURE IX JOHN LIK E IX IX IX "WHO "FUTURE "FUTURE "CAR "CAR "WARY "MARY "MARY "WARY		
### ### ### ### ### ### ### ### ### ##		JOHN ARR
1895		ALL BOY
E GIRL BOX 193: JOHN *SEE *WHO BOX 199: *JOHN CHOCOLATE *JOHN COLATE WHO 201: JOHN *GIVE1 *WOMAN *WOMAN *WRITE HOUSE L MARY IX-1P BUY HOUSE		JOHN CTV
E GIRL BOX 199: *JOHN CHOCOLATE *JOHN 199: *JOHN CHOCOLATE *JOHN 199: *JOHN GIVE1 *WOMAN *WOMAN *WRITE HOUSE 201: JOHN *GIVE1 *WOMAN *WOMAN *WRITE HOUSE L MARY IX-1P BUY HOUSErunning: ['polar-rr', 'polar-rtheta', 'polar-lr', 'polar-ltheta'] <class 'my_model_selectors.selectorconstant'=""> **** WER = 0.61797752808988876 Total correct: 68 out of 178 Video Recognized 2: *GO WRITE HOMEWORK JOHN WRI TE HOMEWORK 7: JOHN *WHAT *MARY *WHAT GO CAN 12: JOHN *WHAT *MARY *WHAT GO CAN 12: JOHN *WHAT *GOI CAN GO CAN 21: *IX *HOMEWORK WONT *FUTURE *CAR *CAR *GO *TOMORROW JOHN CAN GO CAN 21: *IX *HOMEWORK WONT *FUTURE *CAR *CAR *GO *TOMORROW JOHN LIK E IX IX IX 38: *SHOULD LIKE *GO *MARY *GO EIX IX IX 38: *SHOULD LIKE *GO *MARY *GO ETABLE KNOW IX LIKE CORNI 49: *SUE *GIVE *DECIDE MARY *GO THINK MARY LOVE 43: *IX *GO BUY HOUSE 59: *POSS *SEE BUY CAR *ARRIVE OHN BUY CAR SHOULD 54: JOHN SHOULD 55: *MARY *PREFER *MARY MARY IDE VISIT MARY 77: *IX MARY 78: *WARY *PREFER *MARY MARY 1DE VISIT MARY 76: *LIKE *MOTHER NOT BUY HOUSE TIVE NOT BUY HOUSE 71: JOHN *FINISH *GIVEI MARY 72: *GO *WHO *GO VISIT MARY 74: *GO *WHO *GO VISIT MARY 77: *IX BLAME *LOVE 84: *HOMEWORK *GIVEI *POSS BOOK *IX-1P FI N SOMETHING-ONE SEE BUY CAR *ARRIVE A: *IX *GO *WHO *GO *GO VISIT MARY 74: *GO *WHO *GO *GO VISIT MARY 77: *IX BLAME *LOVE AIN BUY HOUSE 77: *IX BLAME *LOVE ANN BLAM *IX-1P FI N SOMETHING-ONE BOOK</class>		JOHN GIV
1991		JOHN GIV
201: JOHN *GIVE1 *WOMAN *WOMAN *WRITE HOUSE		LIKE CHO
L MARY IX-1P BUY HOUSErunning: ['polar-rr', 'polar-rtheta', 'polar-lr', 'polar-ltheta'] <class 'my_model_selectors.selectorconstant'=""> **** WER = 0.6179775280898876 Total correct: 68 out of 178 Video Recognized Correct</class>		
<pre>"my_model_selectors.SelectorConstant'> **** WER = 0.6179775280898876 Total correct: 68 out of 178 Video Recognized</pre>		JOHN TEL
<pre>"my_model_selectors.SelectorConstant'> **** WER = 0.6179775280898876 Total correct: 68 out of 178 Video Recognized</pre>	running: ['polar-rr', 'polar-rtheta', 'polar-lr', 'polar-ltheta'	'] <class< td=""></class<>
Total correct: 68 out of 178		-
Total correct: 68 out of 178	**** WFR = 0 6179775280898876	
Video Recognized		
2: *GO WRITE HOMEWORK T: JOHN *WHAT *MARY *WHAT GO CAN 12: JOHN *WHAT *GO1 CAN GO CAN 12: JOHN *WHAT *GO1 CAN GO CAN 21: *IX *HOMEWORK WONT *FUTURE *CAR *CAR *GO *TOMORROW 21: *IX *HOMEWORK WONT *FUTURE *CAR *CAR *GO *TOMORROW 30: *STRANK LIKE IX *WHO IX E IX IX IX 28: *IX *WHO *FUTURE *FUTURE IX E IX IX IX 30: *SHOULD LIKE *GO *MARY *GO E IX IX IX 36: *SOMETHING-ONE VEGETABLE *GIRL *GIVE *MARY *MARY MARY VEG ETABLE KNOW IX LIKE CORNI 40: *SUE *GIVE *DECIDE MARY *GO THINK MARY LOVE 43: *IX *GO BUY HOUSE 50: *POSS *SEE BUY CAR *ARRIVE OHN BUY CAR SHOULD 54: JOHN SHOULD *WHO BUY HOUSE ULD NOT BUY HOUSE 57: *MARY *PREFER *MARY MARY TOE *MARY TOE *		Correct
2: *GO WRITE HOMEWORK TE HOMEWORK 7: JOHN *WHAT *MARY *WHAT GO CAN 12: JOHN *WHAT *GO1 CAN GO CAN 21: *IX *HOMEWORK WONT *FUTURE *CAR *CAR *GO *TOMORROW 10: *IX *HOMEWORK WONT *FUTURE *CAR *CAR *GO *TOMORROW 21: *IX *HOMEWORK WONT *FUTURE *CAR *CAR *GO *TOMORROW 25: *FRANK LIKE IX *WHO IX 25: *FRANK LIKE IX *WHO IX 28: *IX *WHO *FUTURE *FUTURE IX 28: *IX *WHO *FUTURE *FUTURE IX 28: *IX *WHO *FUTURE *FUTURE IX 30: *SOMETHING-ONE VEGETABLE *GIRL *GIVE *MARY *MARY *** *GO** *** *GO**		
TE HOMEWORK 7: JOHN *WHAT *MARY *WHAT 60 CAN 12: JOHN *WHAT *GO1 CAN GO CAN 21: *IX *HOMEWORK WONT *FUTURE *CAR *CAR *GO *TOMORROW		
7: JOHN *WHAT *MARY *WHAT GO CAN 12: JOHN *WHAT *GO1 CAN GO CAN 21: *IX *HOMEWORK WONT *FUTURE *CAR *CAR *GO *TOMORROW A1: *IX *HOMEWORK WONT *FUTURE *CAR *CAR *GO *TOMORROW A1: *IX *HOMEWORK WONT *FUTURE *CAR *CAR *GO *TOMORROW A2: *IX *MO EAT BUT CAN EAT CHICKEN A2: *IX IX IX A3: *IX *WHO *FUTURE *FUTURE IX BIX IX IX A3: *SOMETHING-ONE VEGETABLE *GIRL *GIVE *MARY *MARY A4: *SUE *GIVE *DECIDE MARY *GO BIANN MARY LOVE A3: *IX *GO BUY HOUSE THINK MARY LOVE A3: *IX *GO BUY HOUSE TOHN BUY CAR SHOULD S4: JOHN SHOULD S5: *POSS *SEE BUY CAR *ARRIVE OHN BUY CAR SHOULD S5: *MARY *PREFER *MARY MARY IDE VISIT MARY 67: *LIKE *MOTHER NOT BUY HOUSE 71: JOHN *FINISH *GIVE1 MARY 74: *GO *WHO *GO *GO VISIT MARY 77: *IX BLAME *LOVE E MARY 84: *HOMEWORK *GIVE1 *POSS BOOK IX-1P FI ND SOMETHING-ONE BOOK		JOHN WRI
12: JOHN *WHAT *GO1 CAN 12: JOHN *WHAT *GO1 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 E IX IX IX 28: *IX *WHO *FUTURE *FUTURE IX E IX IX IX 36: *SOMETHING-ONE VEGETABLE *GIRL *GIVE *MARY *MARY A6: *SUB *GIVE *DECIDE MARY *GO ETABLE KNOW IX LIKE CORN1 40: *SUB *GIVE *DECIDE MARY *GO THINK MARY LOVE 43: *IX *GO BUY HOUSE 50: *POSS *SEE BUY CAR *ARRIVE OHN BUY CAR SHOULD S4: JOHN SHOULD *WHO BUY HOUSE JOHN SHO ULD NOT BUY HOUSE 57: *MARY *PREFER *MARY MARY IDE VISIT MARY 67: *LIKE *MOTHER NOT BUY HOUSE JOHN WIL L VISIT MARY 74: *GO *WHO *GO *GO VISIT MARY 77: *IX BLAME *LOVE EMARY 84: *HOMEWORK *GIVE1 *POSS BOOK IX-1P FI ND SOMETHING-ONE BOOK		JOHN CAN
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122: JOHN *GIVE1 BOOK D BOOK	JOHN REA
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142: *FRANK BUY YESTERDAY WHAT BOOK	JOHN BUY
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89: *GIVE *GIVE *WOMAN *WOMAN IX *ARRIVE *BREAK-DOWN GIVE MAN IX NEW COAT 90: JOHN *HAVE IX SOMETHING-ONE *VISIT *BREAK-DOWN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *WOMAN IX *WOMAN WOMAN BOOK IOO: POSS NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *VEGETABLE 107: JOHN *IX *HAVE *GO *JANA S FRIEND HAVE CANDY 108: *JOHN *HOMEWORK RIVE 113: IX CAR *IX *IX *BUY1 LUE SUE BUY 119: *PREFER *BUY1 *CAR CAR *GO IX CAR BLUE 122: JOHN *GIVE1 BOOK D BOOK 139: JOHN *BUY1 WHAT *BLAME *CHOCOLATE WHAT YESTERDAY BOOK 142: JOHN BUY YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK 158: LOVE JOHN WHO N WHO	JOHN GIV JOHN GIV POSS NEW JOHN LEG JOHN POS WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH
89: *GIVE *GIVE *WOMAN *WOMAN IX *ARRIVE *BREAK-DOWN GIVE MAN IX NEW COAT 90: JOHN *HAVE IX SOMETHING-ONE *VISIT *BREAK-DOWN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *WOMAN IX *WOMAN WOMAN BOOK 100: POSS NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *VEGETABLE 107: JOHN *IX *HAVE *GO *JANA S FRIEND HAVE CANDY 108: *JOHN *HOMEWORK RIVE 113: IX CAR *IX *IX *BUY1 LUE SUE BUY 119: *PREFER *BUY1 *CAR CAR *GO IX CAR BLUE 122: JOHN *GIVE1 BOOK D BOOK 139: JOHN *BUY1 WHAT *BLAME *CHOCOLATE WHAT YESTERDAY BOOK 142: JOHN BUY YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK 158: LOVE JOHN WHO N WHO 167: JOHN IX *VISIT LOVE MARY	JOHN GIV JOHN GIV POSS NEW JOHN LEG JOHN POS WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY
89: *GIVE *GIVE *WOMAN *WOMAN IX *ARRIVE *BREAK-DOWN GIVE MAN IX NEW COAT 90: JOHN *HAVE IX SOMETHING-ONE *VISIT *BREAK-DOWN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *WOMAN IX *WOMAN WOMAN BOOK IOO: POSS NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *VEGETABLE 107: JOHN *IX *HAVE *GO *JANA S FRIEND HAVE CANDY 108: *JOHN *HOMEWORK RIVE 113: IX CAR *IX *IX *BUY1 LUE SUE BUY 119: *PREFER *BUY1 *CAR CAR *GO IX CAR BLUE 122: JOHN *GIVE1 BOOK D BOOK 139: JOHN *BUY1 WHAT *BLAME *CHOCOLATE WHAT YESTERDAY BOOK 142: JOHN BUY YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK 158: LOVE JOHN WHO N WHO	JOHN GIV JOHN GIV POSS NEW JOHN LEG JOHN POS WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH

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Y BLAME
 174: *JOHN *GIVE3 GIVE1 *YESTERDAY *JOHN
                                                                  PEOPLE G
ROUP GIVE1 JANA TOY
 181: *EAT ARRIVE
                                                                  JOHN ARR
IVE
 184: ALL BOY *GIVE1 TEACHER APPLE
                                                                  ALL BOY
GIVE TEACHER APPLE
 189: *MARY *VISIT *VISIT BOX
                                                                  JOHN GIV
E GIRL BOX
 193: JOHN *POSS *VISIT BOX
                                                                  JOHN GIV
E GIRL BOX
 199: *HOMEWORK *VIDEOTAPE *JOHN
                                                                  LIKE CHO
COLATE WHO
 201: JOHN *MAN *MAN *LIKE 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
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84: *HOMEWORK *GIVE1 *GIVE1 *COAT	IX-1P FI
ND SOMETHING-ONE BOOK 89: *GIVE *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	IX CAR B
LUE SUE BUY 119: *MARY *BUY1 IX *BLAME *IX	SUE BUY
IX CAR BLUE 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 GIVE TEACHER APPLE	ALL BOY
189: *MARY *GO *YESTERDAY BOX E GIRL BOX	JOHN GIV
193: JOHN *GO *YESTERDAY BOX E GIRL BOX	JOHN GIV
199: *JOHN *STUDENT *GO COLATE WHO	LIKE CHO
201: JOHN *MAN *LOVE *JOHN BUY HOUSE	JOHN TEL
<pre>L MARY IX-1P BUY HOUSErunning: ['polar-rr', 'polar-rtheta', 'polar-lr', 'polar-ltheta' 'my_model_selectors.SelectorCV'></pre>] <class< td=""></class<>
**** WER = 0.601123595505618	
Total correct: 71 out of 178 Video Recognized	Correct
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2: *POSS WRITE HOMEWORK TE HOMEWORK	JOHN WRI
7: JOHN *HAVE GO *WHAT GO CAN	JOHN CAN

12: *IX *MANY *WHAT CAN	JOHN CAN
GO CAN 21: JOHN *NEW *HOMEWORK *JOHN *CAR *CAR *CHICAGO *TOMORROW	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN 25: JOHN LIKE *LOVE *JOHN IX	JOHN LIK
E IX IX IX 28: JOHN *JOHN *MARY *JOHN IX	JOHN LIK
E IX IX	JOHN LIK
30: JOHN LIKE IX *LIKE *SHOOT E IX IX IX	JOHN LIK
36: MARY VEGETABLE *GIRL *GIVE2 *MARY *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1 40: JOHN *GIVE *CORN *SAY-1P *SHOOT	JOHN IX
THINK MARY LOVE	JOHN IX
43: JOHN *HIT BUY HOUSE	JOHN MUS
T BUY HOUSE	
50: *FRANK *SEE BUY *MANY *WHAT	FUTURE J
OHN BUY CAR SHOULD	JOHN CHO
54: JOHN SHOULD *WHO BUY HOUSE ULD NOT BUY HOUSE	JOHN SHO
57: *IX *SEE *GIVE *IX	JOHN DEC
IDE VISIT MARY	301111 DEC
67: JOHN *JOHN NOT BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE 71: JOHN *FINISH *GO *BLAME	JOHN WIL
L VISIT MARY	JOHN WIL
74: *IX *IX *MARY *GO	JOHN NOT
VISIT MARY 77: *JOHN BLAME *SOMETHING-ONE	ANN BLAM
E MARY 84: *FRANK *ARRIVE *HOMEWORK BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	
89: *GIVE IX *WOMAN *IX IX *ARRIVE *BOOK	JOHN IX
GIVE MAN IX NEW COAT	
90: JOHN *GIVE1 *WOMAN *WOMAN WOMAN *CHOCOLATE	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
92: JOHN *WOMAN IX *WOMAN *SOMETHING-ONE BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
100: POSS NEW CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN 105: JOHN *FRANK	JOHN LEG
107: JOHN *GIVE *HAVE *GO CANDY	JOHN LEG JOHN POS
S FRIEND HAVE CANDY	JOHN POS
108: *MARY *LOVE	WOMAN AR
RIVE	7.07.2.4.4.7.4.4
113: *GO *HAVE *GO *MARY *BUY1	IX CAR B
LUE SUE BUY	
119: *VEGETABLE *BUY1 *GO *HAVE *GIVE IX CAR BLUE	SUE BUY
122: JOHN *HOUSE BOOK	JOHN REA
D BOOK 139: JOHN *BUY1 *TOY YESTERDAY *LAST-WEEK	
WHAT YESTERDAY BOOK	JOHN BUY
142: JOHN *NEW YESTERDAY *MANY BOOK	JOHN BUY
	JOHN BUY
YESTERDAY WHAT BOOK	JOHN BUY

167: JOHN *MARY *SAY-1P *WOMAN *GO	JOHN IX
SAY LOVE MARY 171: JOHN MARY BLAME Y BLAME	JOHN MAR
174: *CAN GROUP GIVE1 *GIRL *WHAT	PEOPLE G
ROUP GIVE1 JANA TOY 181: *VISIT *BOX	JOHN ARR
IVE 184: *WOMAN *YESTERDAY *BLAME TEACHER *GIRL GIVE TEACHER APPLE	ALL BOY
189: JOHN GIVE *YESTERDAY *CAN	JOHN GIV
E GIRL BOX 193: JOHN *GIVE1 *YESTERDAY BOX E GIRL BOX	JOHN GIV
199: *FRANK CHOCOLATE *FRANK	LIKE CHO
COLATE WHO 201: JOHN *SHOULD *WOMAN *LOVE BUY HOUSE L MARY IX-1P BUY HOUSE	JOHN TEL
running: ['delta-rx', 'delta-ry', 'delta-lx', 'delta-ly'] <class l_selectors.selectorconstant'=""></class>	'my_mode
**** WER = 0.6404494382022472	
Total correct: 64 out of 178	Connect
Video Recognized	Correct
2: JOHN *JOHN HOMEWORK	JOHN WRI
TE HOMEWORK	JOHN WILL
7: JOHN *HAVE *GIVE1 *TEACHER GO CAN	JOHN 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	JOHN LIK
E IX IX IX 28: JOHN *MARY *MARY IX IX	JOHN LIK
E IX IX 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	MAKT VLG
40: *MARY IX *MARY MARY *MARY	JOHN IX
THINK MARY LOVE 43: JOHN *JOHN *FINISH HOUSE	JOHN MUS
T BUY HOUSE 50: *JOHN JOHN BUY CAR *MARY	FUTURE J
OHN BUY CAR SHOULD	
54: JOHN *MARY *MARY BUY HOUSE ULD NOT BUY HOUSE	JOHN SHO
57: JOHN *JOHN *IX *JOHN IDE VISIT MARY	JOHN DEC
67: JOHN *JOHN BUY HOUSE URE NOT BUY HOUSE	JOHN FUT
71: JOHN *JOHN VISIT MARY	JOHN WIL
L VISIT MARY 74: JOHN *JOHN *MARY MARY	JOHN NOT

VISIT MARY	
77: *JOHN BLAME MARY	ANN BLAM
E MARY	TV 1D FT
84: *JOHN *GO *IX *WHAT ND SOMETHING-ONE BOOK	IX-1P FI
89: *GIVE1 *JOHN *IX *JOHN IX *WHAT *HOUSE	JOHN IX
GIVE MAN IX NEW COAT	
90: *MARY *JOHN *JOHN *IX *IX *MARY	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
92: JOHN *MARY *JOHN *JOHN WOMAN *ARRIVE	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	DOCC NEU
100: *JOHN NEW *WHAT BREAK-DOWN CAR BREAK-DOWN	POSS NEW
105: JOHN *MARY	JOHN LEG
107: JOHN POSS FRIEND *LOVE *MARY	JOHN POS
S FRIEND HAVE CANDY	30
108: *JOHN ARRIVE	WOMAN AR
RIVE	
113: *JOHN CAR *MARY *MARY *GIVE1	IX CAR B
LUE SUE BUY	
119: *JOHN *BUY1 IX CAR *IX	SUE BUY
IX CAR BLUE	701N DEA
122: JOHN *VISIT *YESTERDAY D BOOK	JOHN REA
139: JOHN *BUY1 WHAT *MARY *ARRIVE	JOHN BUY
WHAT YESTERDAY BOOK	JOHN BOT
142: JOHN BUY *MARY *YESTERDAY	JOHN BUY
YESTERDAY WHAT BOOK	
158: *BOY *WHO *MARY	LOVE JOH
N WHO	
167: *MARY *MARY *IX *ARRIVE *WHAT	JOHN IX
SAY LOVE MARY	
171: JOHN *JOHN BLAME	JOHN MAR
Y BLAME 174: *GIVE1 *MARY GIVE1 *MARY *FINISH	PEOPLE G
ROUP GIVE1 JANA TOY	PEOPLE G
181: JOHN *GIVE1	JOHN ARR
IVE	3011171111
184: *IX *WHO *GIVE1 *HAVE *MARY	ALL BOY
GIVE TEACHER APPLE	
189: JOHN *IX *MARY *VISIT	JOHN GIV
E GIRL BOX	
193: JOHN *IX *IX BOX	JOHN GIV
E GIRL BOX 199: *JOHN *ARRIVE *MARY	LIKE CHO
COLATE WHO	LIKE CHO
201: JOHN *MARY MARY *LIKE *VISIT 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.SelectorBIC'></pre>	
**** LIED 0.6470775200066575	
**** WER = 0.6179775280898876	
Total correct: 68 out of 178 Video Recognized	Correct
video kecognized	
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2: JOHN *LOVE HOMEWORK

TE HOMEHORY	
TE HOMEWORK 7: JOHN *STUDENT *GIVE1 *STUDENT	JOHN CAN
GO CAN	JOHN CAN
12: JOHN CAN *GO1 CAN	JOHN CAN
GO CAN	
21: *MARY *MARY WONT *MARY *CAR *TOMORROW *FUTURE *MARY	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	
25: JOHN *IX *MARY IX IX	JOHN LIK
E IX IX IX	JOHN LTK
28: JOHN *MARY *JOHN IX *SHOULD F TX TX TX	JOHN LIK
30: JOHN *IX IX *JOHN IX	JOHN LIK
E IX IX IX	30 22
36: *JOHN *JOHN IX *MARY *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1	
40: *MARY IX *JOHN MARY *MARY	JOHN IX
THINK MARY LOVE	
43: JOHN *IX *FINISH HOUSE	JOHN MUS
T BUY HOUSE	EUTUBE 3
50: *JOHN JOHN BUY CAR *MARY OHN BUY CAR SHOULD	FUTURE J
54: JOHN *JOHN BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	JOHN JHO
57: *MARY *JOHN *IX *IX	JOHN DEC
IDE VISIT MARY	
67: JOHN *JOHN *MARY BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN *MARY VISIT MARY	JOHN WIL
L VISIT MARY	
	TOUR NOT
74: JOHN *JOHN *IX MARY	JOHN NOT
VISIT MARY	
VISIT MARY 77: *JOHN *CAR MARY	JOHN NOT
VISIT MARY	
VISIT MARY 77: *JOHN *CAR MARY E MARY	ANN BLAM
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK	ANN BLAM
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT	ANN BLAM
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN	ANN BLAM
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK	ANN BLAM IX-1P FI JOHN IX JOHN GIV
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK	ANN BLAM IX-1P FI JOHN IX
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK	ANN BLAM IX-1P FI JOHN IX JOHN GIV JOHN GIV
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN NEW CAR BREAK-DOWN	ANN BLAM IX-1P FI JOHN IX JOHN GIV
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN NEW CAR BREAK-DOWN CAR BREAK-DOWN	ANN BLAM IX-1P FI JOHN IX JOHN GIV JOHN GIV POSS NEW
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN NEW CAR BREAK-DOWN	ANN BLAM IX-1P FI JOHN IX JOHN GIV JOHN GIV
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *JOHN	ANN BLAM IX-1P FI JOHN IX JOHN GIV JOHN GIV POSS NEW JOHN LEG
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *JOHN FRIEND *JOHN *MARY	ANN BLAM IX-1P FI JOHN IX JOHN GIV JOHN GIV POSS NEW JOHN LEG
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *JOHN 107: JOHN *JOHN FRIEND *JOHN *MARY S FRIEND HAVE CANDY 108: *JOHN *MOVIE RIVE	ANN BLAM IX-1P FI JOHN IX JOHN GIV JOHN GIV POSS NEW JOHN LEG JOHN POS WOMAN AR
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *JOHN 107: JOHN *JOHN FRIEND *JOHN *MARY S FRIEND HAVE CANDY 108: *JOHN *MOVIE RIVE 113: *JOHN CAR *MARY *MARY *GIVE1	ANN BLAM IX-1P FI JOHN IX JOHN GIV JOHN GIV POSS NEW JOHN LEG JOHN POS
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *JOHN 107: JOHN *JOHN FRIEND *JOHN *MARY S FRIEND HAVE CANDY 108: *JOHN *MOVIE RIVE 113: *JOHN CAR *MARY *MARY *GIVE1 LUE SUE BUY	ANN BLAM IX-1P FI JOHN IX JOHN GIV JOHN GIV POSS NEW JOHN LEG JOHN POS WOMAN AR IX CAR B
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *JOHN 107: JOHN *JOHN FRIEND *JOHN *MARY S FRIEND HAVE CANDY 108: *JOHN *MOVIE RIVE 113: *JOHN CAR *MARY *MARY *GIVE1 LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY	ANN BLAM IX-1P FI JOHN IX JOHN GIV JOHN GIV POSS NEW JOHN LEG JOHN POS WOMAN AR
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *JOHN 107: JOHN *JOHN FRIEND *JOHN *MARY S FRIEND HAVE CANDY 108: *JOHN *MOVIE RIVE 113: *JOHN CAR *MARY *MARY *GIVE1 LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY IX CAR BLUE	ANN BLAM IX-1P FI JOHN IX JOHN GIV JOHN GIV POSS NEW JOHN LEG JOHN POS WOMAN AR IX CAR B SUE BUY
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *JOHN 107: JOHN *JOHN FRIEND *JOHN *MARY S FRIEND HAVE CANDY 108: *JOHN *MOVIE RIVE 113: *JOHN CAR *MARY *MARY *GIVE1 LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY	ANN BLAM IX-1P FI JOHN IX JOHN GIV JOHN GIV POSS NEW JOHN LEG JOHN POS WOMAN AR IX CAR B
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *JOHN 107: JOHN *JOHN FRIEND *JOHN *MARY S FRIEND HAVE CANDY 108: *JOHN *MOVIE RIVE 113: *JOHN CAR *MARY *MARY *GIVE1 LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY IX CAR BLUE 122: JOHN *ARRIVE *WHAT	ANN BLAM IX-1P FI JOHN IX JOHN GIV JOHN GIV POSS NEW JOHN LEG JOHN POS WOMAN AR IX CAR B SUE BUY
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN NEW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *JOHN 107: JOHN *JOHN FRIEND *JOHN *MARY S FRIEND HAVE CANDY 108: *JOHN *MOVIE RIVE 113: *JOHN CAR *MARY *MARY *GIVE1 LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY IX CAR BLUE 122: JOHN *ARRIVE *WHAT D BOOK	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
VISIT MARY 77: *JOHN *CAR MARY E MARY 84: *JOHN *GIVE1 *IX BOOK ND SOMETHING-ONE BOOK 89: *MARY *JOHN *IX *IX *JOHN *WHAT *CAN GIVE MAN IX NEW COAT 90: JOHN *JOHN *JOHN *IX *IX *JOHN E IX SOMETHING-ONE WOMAN BOOK 92: JOHN *IX *JOHN *IX *IX BOOK E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN EW CAR BREAK-DOWN CAR BREAK-DOWN 105: JOHN *JOHN 107: JOHN *JOHN FRIEND *JOHN *MARY S FRIEND HAVE CANDY 108: *JOHN *MOVIE RIVE 113: *JOHN CAR *MARY *MARY *GIVE1 LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY IX CAR BLUE 122: JOHN *ARRIVE *WHAT D BOOK 139: JOHN *BUY1 WHAT *JOHN *MARY	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

YESTERDAY WHAT BOOK 158: *ARRIVE JOHN *JOHN	LOVE	ЈОН
N WHO		
167: JOHN IX *IX *CAR *WHAT SAY LOVE MARY	JOHN	IX
171: JOHN *JOHN BLAME	JOHN	MAR
Y BLAME 174: *GIVE1 *MARY GIVE1 *MARY *FINISH	PEOPL	E G
ROUP GIVE1 JANA TOY 181: JOHN *GIVE1	JOHN	ARR
IVE 184: *IX *JOHN *GIVE1 *WHO *MARY	ALL E	30Y
GIVE TEACHER APPLE 189: JOHN *JOHN *ARRIVE	JOHN	GTV
E GIRL BOX		
193: JOHN *IX *WOMAN BOX E GIRL BOX	JOHN	GIV
199: *JOHN *WHAT *MARY COLATE WHO	LIKE	СНО
201: JOHN *IX MARY *IX BUY HOUSE	JOHN	TEL
L MARY IX-1P BUY HOUSErunning: ['delta-rx', 'delta-ry', 'delta-lx', 'delta-ly'] <class< td=""><td>'my_n</td><td>node</td></class<>	'my_n	node
l_selectors.SelectorDIC'>		
**** WER = 0.6292134831460674		
Total correct: 66 out of 178	_	
Video Recognized	Corre	
=======================================		
2: JOHN *GIVE1 *ARRIVE TE HOMEWORK	JOHN	WRI
7: JOHN *GIVE1 *GIVE1 *ARRIVE	JOHN	CAN
GO CAN 12: JOHN *BOX *JOHN CAN	JOHN	CAN
GO CAN 21: JOHN *MARY *LOVE *MARY *HOUSE *FUTURE *FUTURE *MARY	JOHN	FIS
H WONT EAT BUT CAN EAT CHICKEN	70111	1 T1/
25: JOHN *IX *JOHN IX IX E IX IX IX	JOHN	LIK
28: JOHN *MARY *JOHN IX *SHOULD E IX IX IX	JOHN	LIK
30: JOHN *IX *SHOULD *JOHN IX	JOHN	LIK
E IX IX IX 36: *JOHN *JOHN IX *MARY *MARY	MARY	VEG
ETABLE KNOW IX LIKE CORN1 40: *MARY IX *JOHN MARY *MARY	JOHN	ΤX
THINK MARY LOVE		
	JOHN	MUS
43: JOHN *IX BUY HOUSE T BUY HOUSE	301114	
T BUY HOUSE 50: *JOHN JOHN BUY CAR *MARY	FUTUF	RE J
T BUY HOUSE 50: *JOHN JOHN BUY CAR *MARY OHN BUY CAR SHOULD 54: JOHN *JOHN BUY HOUSE		
T BUY HOUSE 50: *JOHN JOHN BUY CAR *MARY OHN BUY CAR SHOULD 54: JOHN *JOHN *JOHN BUY HOUSE ULD NOT BUY HOUSE 57: *MARY *JOHN *IX *IX	FUTUF	SH0
T BUY HOUSE 50: *JOHN JOHN BUY CAR *MARY OHN BUY CAR SHOULD 54: JOHN *JOHN *JOHN BUY HOUSE ULD NOT BUY HOUSE	FUTUF	SHO DEC
T BUY HOUSE 50: *JOHN JOHN BUY CAR *MARY OHN BUY CAR SHOULD 54: JOHN *JOHN *JOHN BUY HOUSE ULD NOT BUY HOUSE 57: *MARY *JOHN *IX *IX IDE VISIT MARY	FUTUF JOHN JOHN	SHO DEC

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 DLAM
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	JOHN GIV
92: JOHN *IX *JOHN *IX WOMAN *MARY	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
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	
119: *JOHN *GIVE1 IX CAR *MARY	SUE BUY
IX CAR BLUE	
122: JOHN *GIVE1 *WHAT	JOHN REA
D BOOK	
139: JOHN *GIVE1 WHAT *JOHN *WHAT	JOHN BUY
WHAT YESTERDAY BOOK	301
142: JOHN BUY *FUTURE WHAT *WHAT	JOHN BUY
YESTERDAY WHAT BOOK	JOHN DOT
158: LOVE JOHN *JOHN	LOVE JOH
N WHO	LOVE JOIL
	JOHN TV
167: JOHN IX *IX *WHAT MARY	JOHN IX
SAY LOVE MARY	701111 1445
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	
199: *JOHN *WHAT *MARY	LIKE CHO
COLATE WHO	
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
l selectors.SelectorCV'>	- <u>-</u>
_	
**** WER = 0.6235955056179775	
Total compact, (7 out of 179	

Total correct: 67 out of 178

Video Recognized

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2: JOHN *LOVE HOMEWORK	JOHN WRI
TE HOMEWORK	
7: JOHN *TOY GO *TEACHER	JOHN CAN
GO CAN	TOUR CAN
12: JOHN CAN *GROUP CAN	JOHN CAN
GO CAN 21: *MARY *MARY *LOVE *MARY *BUY *GO *YESTERDAY *MARY	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	JOHN F13
25: JOHN *IX *MARY IX IX	JOHN LIK
E IX IX IX	301111 2211
28: JOHN *IX IX IX	JOHN LIK
E IX IX IX	
30: JOHN *IX *WHO *JOHN IX	JOHN LIK
E IX IX IX	
36: *IX *IX *GIVE *MARY *IX	MARY VEG
ETABLE KNOW IX LIKE CORN1	70.00 70
40: *MARY IX *JOHN *IX *IX	JOHN IX
THINK MARY LOVE 43: JOHN *IX BUY HOUSE	JOHN MUS
T BUY HOUSE	JUHN MUS
50: *JOHN *NOT BUY CAR *MARY	FUTURE J
OHN BUY CAR SHOULD	. OTORE 5
54: JOHN *JOHN BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	
57: *WOMAN *JOHN *IX *IX	JOHN DEC
IDE VISIT MARY	
67: JOHN *WHO *IX BUY *LOVE	JOHN FUT
URE NOT BUY HOUSE	70.00
71: JOHN *JOHN VISIT MARY L VISIT MARY	JOHN WIL
74: JOHN *WHO *IX MARY	JOHN NOT
VISIT MARY	301111 1101
77: *JOHN BLAME MARY	ANN BLAM
E MARY	
84: *JOHN *GO *IX *MARY	IX-1P FI
ND SOMETHING-ONE BOOK	
89: *MARY IX GIVE *IX IX *CAR COAT	JOHN IX
GIVE MAN IX NEW COAT	
90: *IX *IX *JOHN *IX *LIKE *MARY	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	JOHN CTV
92: JOHN *IX IX *IX *POSS *GROUP E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
100: *JOHN *GO CAR BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	1033 NEW
105: JOHN *IX	JOHN LEG
107: JOHN POSS *TOY *MARY *MARY	JOHN POS
S FRIEND HAVE CANDY	
108: *JOHN *POTATO	WOMAN AR
RIVE	
113: *JOHN CAR *MARY *JOHN *BUY1	IX CAR B
LUE SUE BUY	CHE BURY
119: *JOHN *BUY1 *GO CAR *MARY	SUE BUY
IX CAR BLUE 122: JOHN *BOX BOOK	JOHN REA
D BOOK	JOHN NEA
5 50011	

139: JOHN *BUY1 WHAT *IX *MARY	JOHN BUY
WHAT YESTERDAY BOOK	301114 201
142: JOHN BUY YESTERDAY WHAT *MARY	JOHN BUY
YESTERDAY WHAT BOOK 158: *GIVE1 *MARY *MARY	LOVE JOH
N WHO	
167: JOHN IX *IX *ARRIVE *WHAT	JOHN IX
SAY LOVE MARY 171: *IX *JOHN BLAME	JOHN MAR
Y BLAME	
174: *GO *MARY GIVE1 *MARY *PEOPLE	PEOPLE G
ROUP GIVE1 JANA TOY 181: JOHN *GIVE1	JOHN ARR
IVE	
184: *GIVE *JOHN *GIVE1 TEACHER *MARY	ALL BOY
GIVE TEACHER APPLE 189: JOHN *IX *JOHN *WHAT	JOHN GIV
E GIRL BOX	00
193: JOHN *IX *LIKE BOX	JOHN GIV
E GIRL BOX 199: *JOHN *BOOK *MARY	LIKE CHO
COLATE WHO	
201: JOHN *IX *IX *LIKE BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSErunning: ['dist-norm-left-right', 'delta-dist-norm-left-right']	<class 'm<="" td=""></class>
y_model_selectors.SelectorConstant'>	
**** 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 JOHN CAN JOHN CAN
Video Recognized ===================================	JOHN WRI
Video Recognized ====================================	JOHN WRI JOHN CAN JOHN CAN
Video Recognized ===================================	JOHN WRI JOHN CAN JOHN CAN JOHN FIS JOHN LIK
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
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
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 CAN JOHN FIS JOHN LIK JOHN LIK JOHN LIK MARY VEG
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 CAN JOHN FIS JOHN LIK JOHN LIK MARY VEG JOHN IX JOHN MUS FUTURE J
Video Recognized ===================================	JOHN WRI JOHN CAN JOHN CAN JOHN FIS 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 JOHN MUS FUTURE J

IDE VISIT MARY 67: *WONT FUTURE NOT BUY *CAN	JOHN FUT
LIDE NOT DIN HOUSE	
URE NOT BUY HOUSE 71: *BUY WILL *JOHN *VISIT	JOHN WIL
L VISIT MARY	
74: *TOY1 *CANDY *NOT *PREFER VISIT MARY	JOHN NOT
77: ANN *STUDENT *BUT	ANN BLAM
E MARY 84: *BROTHER *BUY1 *ARRIVE *SAY	IX-1P FI
ND SOMETHING-ONE BOOK 89: *YESTERDAY *PUTASIDE *GO1 *SOMETHING-ONE *HOUSE *SHOOT	Γ *BOOK JOHN IX
GIVE MAN IX NEW COAT	
90: *VEGETABLE *FUTURE *G01 *ALL *HAVE BOOK E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
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	
105: *SEE *GIRL 107: *LIKE *NEW *ARRIVE *WONT *SAY-1P	JOHN LEG JOHN POS
S FRIEND HAVE CANDY	301111 1 03
108: *NEXT-WEEK *SOMETHING-ONE RIVE	WOMAN AR
113: *SHOOT *BOX *VEGETABLE *NOT *BUY1	IX CAR B
LUE SUE BUY 119: *JANA *BUY1 *LOVE *HOMEWORK *FRIEND	SUE BUY
IX CAR BLUE	302 001
122: *BUY *ARRIVE *APPLE D BOOK	JOHN REA
139: *WONT *BUY1 *LOVE *G01 BOOK	JOHN BUY
WHAT YESTERDAY BOOK	70UN DUN
142: *BREAK-DOWN *FRIEND *CHICAGO WHAT *CORN YESTERDAY WHAT BOOK	JOHN BUY
158: *BLAME *BOY *PREFER	LOVE JOH
N WHO	JOHN TV
167: *WONT *BUY *SAY-1P LOVE *BOY SAY LOVE MARY	JOHN IX
171: *LIKE *MOTHER BLAME	JOHN MAR
Y BLAME 174: *ARRIVE *YESTERDAY *CAR *CORN1 *LOVE	PEOPLE G
ROUP GIVE1 JANA TOY	70111 400
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 E GIRL BOX	JOHN GIV
199: *OLD *WONT *SEE	LIKE CHO
COLATE WHO 201: JOHN *THINK *COAT *NOT BUY *GIVE	JOHN TEL
L MARY IX-1P BUY HOUSE	JOHN ILL
running: ['dist-norm-left-right', 'delta-dist-norm-left-r	right'] <class 'm<="" td=""></class>
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**** WER = 0.8089887640449438 Total correct: 34 out of 178

SUE BUY

Video Recognized	Correct
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2: *FUTURE *ARRIVE *CHOCOLATE	JOHN WRI
TE HOMEWORK	
7: *JANA *BUY1 *BLUE *FRIEND	JOHN CAN
GO CAN	70.0.
12: *BUY *BUT *WHAT *WHAT	JOHN CAN
GO CAN 21: JOHN *TOY1 *WHO *JOHN *BLAME *BLAME *JOHN *JOHN	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	JOHN FIS
25: *TEACHER *VIDEOTAPE *CAN *NEW *PUTASIDE	JOHN LIK
E IX IX IX	JOHN LIK
28: *BREAK-DOWN *GIVE *GO1 *MAN *WANT	JOHN LIK
E IX IX IX	301 22
30: *WHO *MOTHER *PAST *SHOULD *TELL	JOHN LIK
E IX IX IX	
36: *JOHN *FIND KNOW *PREFER *CANDY *JOHN	MARY VEG
ETABLE KNOW IX LIKE CORN1	
40: *TOY1 *SOMETHING-ONE *CORN1 *BROCCOLI *JOHN	JOHN IX
THINK MARY LOVE	
43: JOHN *GIRL BUY *CAN	JOHN MUS
T BUY HOUSE	
50: *PAST *BREAK-DOWN *BUY1 CAR *MARY	FUTURE J
OHN BUY CAR SHOULD	JOHN CHO
54: *MOVIE *SELF *GIRL BUY HOUSE ULD NOT BUY HOUSE	JOHN SHO
57: JOHN *PREFER *IX *BREAK-DOWN	JOHN DEC
IDE VISIT MARY	JOHN DEC
67: JOHN *IX *CHICKEN BUY *CAN	JOHN FUT
URE NOT BUY HOUSE	
71: *BUY *SHOULD *JOHN *VISIT	JOHN WIL
L VISIT MARY	
74: *MOVIE *SUE *JOHN *NEW-YORK	JOHN NOT
VISIT MARY	
77: *SUE *STUDENT *CAN	ANN BLAM
E MARY	
84: *BROTHER *BUY1 *WRITE *SAY	IX-1P FI
ND SOMETHING-ONE BOOK	
89: *YESTERDAY *YESTERDAY *GO1 *SOMETHING-ONE *HOUSE *CHICAGO *	BOOK JOHN
IX GIVE MAN IX NEW COAT 90: *VEGETABLE *FUTURE *GO1 SOMETHING-ONE *JOHN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	JOHN GIA
92: JOHN *YESTERDAY *WHAT *WHAT *TEACHER BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	JOINT GIV
100: *IX NEW *STOLEN BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	
105: JOHN *GIRL	JOHN LEG
107: JOHN *BLAME *ARRIVE *JOHN *JOHN	JOHN POS
S FRIEND HAVE CANDY	
108: *FRIEND *JOHN	WOMAN AR
RIVE	
113: *JOHN *BOX *GIVE *SHOULD *BUY1	IX CAR B
LUE SUE BUY	

119: *JANA *BUY1 *TOY *HOMEWORK *POSS

IX CAR BLUE	
122: JOHN *IX *APPLE	JOHN REA
D BOOK	70.00
139: JOHN *BUY1 *LOVE *WHAT BOOK WHAT YESTERDAY BOOK	JOHN BUY
142: *EAT *FRIEND YESTERDAY WHAT *CORN	JOHN BUY
YESTERDAY WHAT BOOK	10/5 7011
158: *WHAT *PEOPLE *FRANK N WHO	LOVE JOH
167: JOHN *JOHN *IX-1P LOVE *MAN	JOHN IX
SAY LOVE MARY	701111 1445
171: *LIKE *JOHN BLAME Y BLAME	JOHN MAR
174: *TOY *KNOW *CAR *CORN1 *LOVE	PEOPLE G
ROUP GIVE1 JANA TOY	
181: *TEACHER ARRIVE IVE	JOHN ARR
184: *GIVE1 *WHO *GIVE1 *TOY *PREFER	ALL BOY
GIVE TEACHER APPLE	
189: JOHN *JOHN *PREFER BOX E GIRL BOX	JOHN GIV
193: JOHN *JOHN GIRL *CAR	JOHN GIV
E GIRL BOX	
199: *OLD CHOCOLATE *SEE COLATE WHO	LIKE CHO
201: JOHN *THINK *KNOW *MARY BUY *GIVE	JOHN TEL
L MARY IX-1P BUY HOUSE	
<pre>running: ['dist-norm-left-right', 'delta-dist-norm-left-right'] y_model_selectors.SelectorDIC'></pre>	<class 'm<="" td=""></class>
y_model_selectors.selectorsle /	
**** WER = 0.8370786516853933	
**** WER = 0.8370786516853933 Total correct: 29 out of 178	Connect
**** WER = 0.8370786516853933	Correct
**** 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 ====================================	=======
**** 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
**** 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 JOHN LIK
**** 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
**** 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
**** 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'>

108: *BOOK *JOHN

RIVE

Correct

WOMAN AR

Video Recognized	Correct
	========
2: JOHN *ARRIVE *CHOCOLATE	JOHN WRI
TE HOMEWORK	
7: JOHN *BUY *MARY CAN	JOHN CAN
GO CAN	
12: JOHN *BUT *THROW *HOUSE	JOHN CAN
GO CAN 21: JOHN *TOY1 *WHO *JANA *WHAT *BLAME *SHOULD *JOHN	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	JOHN LT2
25: *GIVE1 *NEXT-WEEK *HOUSE *GIVE1 *WHAT	JOHN LIK
E IX IX IX	00 ==
28: *MAN *GIRL *HOUSE *GIVE1 *HOUSE	JOHN LIK
E IX IX IX	
30: *WHO *MOTHER *JOHN *SHOULD *TELL	JOHN LIK
E IX IX IX	
36: *JOHN *JOHN *GIRL *LOVE *CANDY *JOHN	MARY VEG
ETABLE KNOW IX LIKE CORN1 40: *TOY1 *NEW *CORN *NEW-YORK *MARY	JOHN IX
THINK MARY LOVE	JOHN IX
43: *YESTERDAY *GIRL BUY HOUSE	JOHN MUS
T BUY HOUSE	50
50: *PREFER *PREFER *BUY1 *WHAT *JOHN	FUTURE J
OHN BUY CAR SHOULD	
54: *MOTHER *SELF *CORN *JOHN HOUSE	JOHN SHO
ULD NOT BUY HOUSE	
57: *NOT *SELF *IX *BREAK-DOWN	JOHN DEC
IDE VISIT MARY 67: JOHN *YESTERDAY *VISIT BUY *CAN	JOHN FUT
URE NOT BUY HOUSE	JOHN FOT
71: JOHN *THINK *BUY1 *FUTURE	JOHN WIL
L VISIT MARY	
74: *MOTHER *CANDY *MARY *PREFER	JOHN NOT
VISIT MARY	
77: ANN *LOVE *G01	ANN BLAM
E MARY	TV 4D FT
84: *BOY *BUY1 SOMETHING-ONE *GIRL ND SOMETHING-ONE BOOK	IX-1P FI
89: *BOOK *YESTERDAY *CAN *SOMETHING-ONE *HOUSE *IX *BOOK	JOHN IX
GIVE MAN IX NEW COAT	301114 17
90: *VEGETABLE *GIVE1 *GO1 *MAN WOMAN *CAN	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
92: JOHN *YESTERDAY *WHAT *WHAT *VIDEOTAPE BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
100: *LOVE *VIDEOTAPE *WHAT BREAK-DOWN	POSS NEW
CAR BREAK-DOWN	70UN 150
105: *WHO *GIRL 107: JOHN *BLAME *BUY1 *JOHN *MARY	JOHN LEG JOHN POS
S FRIEND HAVE CANDY	JUHN PUS
100 *POOK *JOIN	LIOMANI AD

113: *JOHN *NEW *MARY *NOT *BUY1	IX CAR B
LUE SUE BUY 119: *JANA *BUY1 *LOVE *FINISH *CHICAGO IX CAR BLUE	SUE BUY
122: JOHN *LOVE *CHINA D BOOK	JOHN REA
139: JOHN *ARRIVE *GIVE1 *THROW *DECIDE WHAT YESTERDAY BOOK	JOHN BUY
142: *VISIT *LOVE YESTERDAY WHAT *CORN YESTERDAY WHAT BOOK	JOHN BUY
158: *BLAME *ARRIVE *NEW-YORK N WHO	LOVE JOH
167: JOHN *BUY1 *CANDY *CAN MARY SAY LOVE MARY	JOHN IX
171: *LIKE *JOHN BLAME Y BLAME	JOHN MAR
174: *BOX *THINK *BLAME *NEW-YORK *GO ROUP GIVE1 JANA TOY	PEOPLE G
181: *HOUSE *LOVE	JOHN ARR
184: *GIVE1 BOY *GIVE1 TEACHER *PREFER GIVE TEACHER APPLE	ALL BOY
189: *JANA *MARY *IX BOX E GIRL BOX	JOHN GIV
193: JOHN *YESTERDAY GIRL *GIVE1 E GIRL BOX	JOHN GIV
199: *VISIT CHOCOLATE *BLUE COLATE WHO	LIKE CHO
201. JOHN *MOTHER *THINK *CHICKEN BUY HOUSE	
201: JOHN *MOTHER *THINK *CHICKEN 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', 'delty'] <class 'my_model_selectors.selectorconstant'=""> **** WER = 0.5449438202247191</class>	
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>	elta-norm- Correct
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</class>	elta-norm- Correct
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'delta-norm-tx', 'de	elta-norm- Correct
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
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
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
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
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 FIS
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'de'ty'] <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 FIS JOHN LIK JOHN LIK
L MARY IX-1P BUY HOUSErunning: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'de'ty'] <class 'my_model_selectors.selectorconstant'=""> **** WER = 0.5449438202247191 Total correct: 81 out of 178 Video Recognized</class>	Correct JOHN WRI JOHN CAN JOHN FIS JOHN LIK JOHN LIK

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
RIVE 113: *JOHN CAR *MARY *MARY *BUY1 LUE SUE BUY 119: *JOHN *BUY1 IX CAR *MARY IX CAR BLUE 122: JOHN READ *YESTERDAY	IX CAR B
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
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	IX CAR B SUE BUY JOHN REA JOHN BUY 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 YESTERDAY WHAT BOOK 158: LOVE *IX WHO N WHO 167: JOHN IX *LIKE LOVE *HERE	IX CAR B SUE BUY JOHN REA JOHN BUY 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 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
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	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX JOHN MAR
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	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 Y BLAME 174: *CAR *LOVE GIVE1 *WHAT *FINISH ROUP GIVE1 JANA TOY	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX JOHN MAR
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	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX JOHN MAR PEOPLE G
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	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX JOHN MAR PEOPLE G
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	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	IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH JOHN IX JOHN MAR PEOPLE G JOHN ARR
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
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

JOHN TEL

POSS NEW

JOHN LEG

JOHN POS

L MARY IX-1P BUY HOUSE

----running: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'delta-normly'] <class 'my_model_selectors.SelectorBIC'>

**** WER = 0.5449438202247191

Total correct: 81 out of 178

E IX SOMETHING-ONE WOMAN BOOK 100: *JOHN NEW CAR *MANY

107: JOHN *JOHN FRIEND *YESTERDAY *JOHN

CAR BREAK-DOWN 105: JOHN *JOHN

VIUCO	Recognized	COLLECT

Video Recognized	Correct
	========
2: JOHN *IX HOMEWORK	JOHN WRI
TE HOMEWORK	
7: JOHN *PEOPLE GO *TEACHER	JOHN CAN
GO CAN	
12: JOHN *BOX *GO1 CAN	JOHN CAN
GO CAN	
21: JOHN *NAME *HOMEWORK *MARY *BUY *GO *YESTERDAY *MARY	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	
25: JOHN *IX IX IX	JOHN LIK
E IX IX IX	
28: JOHN *MARY IX IX IX	JOHN LIK
E IX IX IX	
30: JOHN *IX IX *JOHN IX	JOHN LIK
E IX IX IX	
36: *JOHN *SEE *IX IX *JOHN *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1	
40: JOHN IX *JOHN MARY *MARY	JOHN IX
THINK MARY LOVE	
43: JOHN *IX *FINISH HOUSE	JOHN MUS
T BUY HOUSE	
50: *JOHN *IX BUY CAR *MARY	FUTURE J
OHN BUY CAR SHOULD	
54: JOHN *JOHN *WHO BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	
57: JOHN *JOHN *IX *IX	JOHN DEC
IDE VISIT MARY	
67: JOHN *IX *WOMAN BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN *JOHN VISIT *CAR	JOHN WIL
L VISIT MARY	
74: JOHN *IX *IX MARY	JOHN NOT
VISIT MARY	
77: *JOHN BLAME MARY	ANN BLAM
E MARY	
84: *JOHN *NEW *IX *BUY1	IX-1P FI
ND SOMETHING-ONE BOOK	
89: JOHN IX *IX *IX NEW COAT	JOHN IX
GIVE MAN IX NEW COAT	
90: JOHN *IX IX *IX *IX *MARY	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
92: JOHN *IX IX *IX WOMAN *FINISH	JOHN GIV

S FRIEND HAVE CANDY	
108: *IX ARRIVE	WOMAN AR
RIVE 113: *JOHN CAR *MARY *IX *BUY1	IX CAR B
LUE SUE BUY	
119: *JOHN *BUY1 *HERE CAR *HAVE IX CAR BLUE	SUE BUY
122: JOHN READ *HERE	JOHN REA
D BOOK	701N BUN
139: JOHN *BUY1 WHAT *JOHN *MARY WHAT YESTERDAY BOOK	JOHN BUY
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	10)/5 3011
158: LOVE JOHN *JOHN N WHO	LOVE JOH
167: JOHN *JOHN *LIKE LOVE *HERE	JOHN IX
SAY LOVE MARY	JOHN MAD
171: *IX *JOHN BLAME Y BLAME	JOHN MAR
174: *VISIT *YESTERDAY GIVE1 *MARY *WANT	PEOPLE G
ROUP GIVE1 JANA TOY	70.00 400
181: JOHN *BUY1 IVE	JOHN ARR
184: *IX *JOHN *GIVE1 TEACHER *MARY	ALL BOY
GIVE TEACHER APPLE	70.00 07.4
189: JOHN *IX *JOHN *ARRIVE E GIRL BOX	JOHN GIV
193: JOHN *IX *IX BOX	JOHN GIV
E GIRL BOX	1 TVE CUO
199: *JOHN *JOHN *MARY COLATE WHO	LIKE CHO
201: JOHN *MARY MARY *SOMETHING-ONE BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	٦.
<pre>running: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'd ly'] <class 'my_model_selectors.selectordic'=""></class></pre>	elta-norm-
Ty] (class my_model_selectors.selectors)	
**** WER = 0.5955056179775281	
Total correct: 72 out of 178 Video Recognized	Correct
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2. 70UN UDITE HOMEHODY	JOHN HOT
2: JOHN WRITE HOMEWORK TE HOMEWORK	JOHN WRI
7: JOHN *HAVE *CAR *VISIT	JOHN CAN
GO CAN	TOUR CAN
12: JOHN *BOX *GO1 CAN GO CAN	JOHN CAN
21: JOHN FISH *GIVE1 *MARY BUT *BLAME *MARY *MARY	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	JOHN LTV
25: JOHN *WHAT *JOHN IX *CORN E IX IX IX	JOHN LIK
28: JOHN *MARY *JOHN *JOHN IX	JOHN LIK
E IX IX IX	70UN 1711
30: JOHN *MARY *PUTASIDE *JOHN IX E IX IX	JOHN LIK
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
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	WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY
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	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 WHAT YESTERDAY BOOK 142: JOHN BUY *JOHN WHAT *CAR YESTERDAY WHAT BOOK 158: *JOHN JOHN *JOHN	WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY
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
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	WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH
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 199: *JOHN *JOHN *MARY COLATE WHO	LIKE CHO
201: JOHN *MARY *JOHN *WOMAN BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	1-14
running: ['delta-norm-rx', 'delta-norm-ry', 'delta-norm-lx', 'delta-norm-lx', 'delta-norm-lx', 'delta-norm-ry', 'delta-norm-lx', 'delta-no	ieita-norm-
**** WER = 0.5730337078651685	
Total correct: 76 out of 178	
Video Recognized	Correct
	:=======
2: JOHN *LOVE HOMEWORK	JOHN WRI
TE HOMEWORK	
7: JOHN *TOY GO *TEACHER	JOHN CAN
GO CAN	JOHN CAN
12: JOHN *BOX *GO1 CAN GO CAN	JOHN CAN
21: JOHN *JOHN *TOMORROW *MARY *BUY *GO *FUTURE *MARY	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	
25: JOHN *IX *YESTERDAY IX IX	JOHN LIK
E IX IX IX	
28: JOHN *IX IX IX E IX IX IX	JOHN LIK
30: JOHN *IX *LOVE *JOHN IX	JOHN LIK
E IX IX IX	JOHN LIK
36: *IX *JOHN *JOHN IX *WHAT *IX	MARY VEG
ETABLE KNOW IX LIKE CORN1	
40: JOHN IX *JOHN *IX *IX	JOHN IX
THINK MARY LOVE 43: JOHN *WOMAN BUY HOUSE	JOHN MUS
T BUY HOUSE	JUHN MUS
50: *JOHN JOHN BUY CAR *FUTURE	FUTURE J
OHN BUY CAR SHOULD	
54: JOHN *IX *IX BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	701N DEC
57: JOHN *JOHN *IX *IX IDE VISIT MARY	JOHN DEC
67: JOHN *JOHN *IX BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN *JOHN VISIT MARY	JOHN WIL
L VISIT MARY	70.0.
74: JOHN *IX *IX MARY VISIT MARY	JOHN NOT
77: *JOHN BLAME MARY	ANN BLAM
E MARY	
84: *ANN *NEW *LOVE BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	70
89: JOHN IX GIVE *IX *MARY *WHAT COAT GIVE MAN IX NEW COAT	JOHN IX
90: *MARY *JOHN *JOHN *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	55 51V
92: JOHN *IX IX *IX *POSS *NEW	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	
100: *JOHN NEW CAR BREAK-DOWN	POSS NEW

CAR BREAK-DOWN	
105: JOHN *IX	JOHN LEG
107: JOHN POSS *ARRIVE *YESTERDAY *JOHN	JOHN POS
S FRIEND HAVE CANDY	
108: *JOHN *HOMEWORK	WOMAN AR
RIVE	
113: *JOHN *PEOPLE *MARY *JOHN *BUY1	IX CAR B
LUE SUE BUY 119: *JOHN *BUY1 *WHAT CAR *FUTURE	SUE BUY
IX CAR BLUE	JOL DOT
122: JOHN *PEOPLE *YESTERDAY	JOHN REA
D BOOK	
139: JOHN *NEW WHAT *JOHN *ARRIVE	JOHN BUY
WHAT YESTERDAY BOOK	
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	10//5 70//
158: LOVE *WHAT *MARY N WHO	LOVE JOH
167: JOHN IX *LOVE *FRIEND *HERE	JOHN IX
SAY LOVE MARY	JOHN IX
171: *IX *JOHN BLAME	JOHN MAR
Y BLAME	
174: *LOVE *JOHN GIVE1 *MARY *PEOPLE	PEOPLE G
ROUP GIVE1 JANA TOY	
181: JOHN *BOOK	JOHN ARR
IVE	ALL DOV
184: *GIVE *JOHN *GIVE1 TEACHER *YESTERDAY GIVE TEACHER APPLE	ALL BOY
189: JOHN *IX *JOHN *ARRIVE	JOHN GIV
E GIRL BOX	301 021
193: JOHN *IX *VISIT BOX	JOHN GIV
E GIRL BOX	
199: *JOHN *JOHN *MARY	LIKE CHO
COLATE WHO	70.0. 75.
201: JOHN *IX *WHO *IX BUY HOUSE L MARY IX-1P BUY HOUSE	JOHN TEL
running: ['norm-polar-rr', 'norm-rtheta', 'norm-polar-lr', 'norm	1-nolan-l+
heta', 'delta-norm-polar-rr', 'delta-norm-rtheta', 'delta-norm-polar	r-1r'. 'de
lta-norm-polar-ltheta'] <class 'my="" model="" selectors.selectorconstant'<="" td=""><td></td></class>	
, , , , , , , , , , , , , , , , , , , ,	
**** WER = 0.4606741573033708	
Total correct: 96 out of 178	
Video Recognized	Correct
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	עדו וא⊔∩ר
25: JOHN *TELL *LOVE *WHO IX E IX IX	JOHN LIK
28: JOHN *WHO *WHO IX	JOHN LIK
E IX IX IX	

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
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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
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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', 'norm heta', 'delta-norm-polar-rr', 'delta-norm-rtheta', 'delta-norm-polar lta-norm-polar-ltheta'] <class 'my_model_selectors.selectorbic'=""></class>	
**** WER = 0.42696629213483145	
Total correct: 102 out of 178	
Video Recognized	Correct
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2: JOHN WRITE HOMEWORK TE HOMEWORK	JOHN WRI
7: JOHN *HAVE *IX *TOY GO CAN	JOHN CAN
12: JOHN CAN *GO1 CAN GO CAN	JOHN CAN
21: JOHN *HOMEWORK WONT *WHO BUT *CAR *CHICKEN CHICKEN	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	
25: JOHN LIKE IX *WHO IX	JOHN LIK
E IX IX IX 28: JOHN *WHO IX IX IX	JOHN LIK
E IX IX IX	JOHN LIK
30: JOHN *MARY *MARY *MARY	JOHN LIK
E IX IX IX	MADY VEC
36: MARY *WHO *GIRL *GIVE *MARY *MARY ETABLE KNOW IX LIKE CORN1	MARY VEG
40: JOHN *BILL *CORN MARY *MARY	JOHN IX
THINK MARY LOVE	
43: JOHN *POSS BUY HOUSE	JOHN MUS
T BUY HOUSE 50: *JOHN *SEE BUY CAR *VIDEOTAPE	FUTURE J
OHN BUY CAR SHOULD	TOTOKE 3
54: JOHN SHOULD *MARY BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	70UN DEC
57: JOHN *PREFER VISIT MARY IDE VISIT MARY	JOHN DEC
67: JOHN *YESTERDAY NOT BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN *FUTURE VISIT MARY L VISIT MARY	JOHN WIL
74: JOHN *WHO *MARY MARY	тои инос
VISIT MARY 77: *JOHN BLAME MARY	ANN BLAM
E MARY 84: *MARY *NEW *HOMEWORK BOOK	IX-1P FI
ND SOMETHING-ONE BOOK 89: JOHN *GIVE *WOMAN *OLD IX *BUY *BOOK	JOHN IX
GIVE MAN IX NEW COAT	J 1/

90: JOHN *GIVE1 IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK 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 *MARY *WHO	JOHN POS
S FRIEND HAVE CANDY	301111 1 03
108: *MAN *BOOK	WOMAN AR
RIVE	
113: IX CAR BLUE *JOHN *IX-1P	IX CAR B
LUE SUE BUY	
119: *JOHN *BUY1 *BLUE *TOY *JANA	SUE BUY
IX CAR BLUE	
122: JOHN READ BOOK	JOHN REA
D BOOK 139: JOHN *BUY1 WHAT YESTERDAY BOOK	JOHN BUY
WHAT YESTERDAY BOOK	JOHN BUT
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	30111 201
158: LOVE *MARY WHO	LOVE JOH
N WHO	
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	JUNIN AKK
184: *GIVE3 BOY *GIVE1 TEACHER *GIRL	ALL BOY
GIVE TEACHER APPLE	ALL DOT
189: JOHN *SELF *CORN *BUY1	JOHN GIV
E GIRL BOX	
193: JOHN *SOMETHING-ONE *GIVE1 BOX	JOHN GIV
E GIRL BOX	
199: *JOHN CHOCOLATE WHO	LIKE CHO
COLATE WHO	70.0. 75.
201: JOHN *MARY *WOMAN *WOMAN BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSErunning: ['norm-polar-rr', 'norm-rtheta', 'norm-polar-lr', 'norm	nolan l+
heta', 'delta-norm-polar-rr', 'delta-norm-rtheta', 'delta-norm-polar	•
lta-norm-polar-ltheta'] <class 'my_model_selectors.selectordic'=""></class>	11 , ac
**** WER = 0.4044943820224719	
Total correct: 106 out of 178	
Video Recognized	Correct
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2. JOHN LIDTTE HOMEHODIC	JOHN JOT
2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK 7: JOHN CAN GO *TOY	JOHN CAN
GO CAN	JUIN CAN
12: JOHN *WHAT *GO1 CAN	JOHN CAN
GO CAN	Joint Crist
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

V DI ME	
Y BLAME 174: PEOPLE GROUP GIVE1 *CORN TOY ROUP GIVE1 JANA TOY	PEOPLE G
181: *SUE ARRIVE	JOHN ARR
IVE 184: ALL BOY *GIVE1 TEACHER *GIRL	ALL BOY
GIVE TEACHER APPLE 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 201: JOHN *MARY *WOMAN *JOHN BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSErunning: ['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 = 0.449438202247191	
Total correct: 98 out of 178 Video Recognized	Correct
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2: JOHN WRITE HOMEWORK TE HOMEWORK	JOHN WRI
7: JOHN CAN GO *TOY GO CAN	JOHN CAN
12: JOHN CAN *GO1 CAN GO CAN	JOHN CAN
21: JOHN FISH *HOMEWORK *WHO BUT *MANY EAT CHICKEN H WONT EAT BUT CAN EAT CHICKEN	JOHN FIS
25: JOHN LIKE *MARY *WHO IX	JOHN LIK
E IX IX IX 28: JOHN *WHO *MARY *WHO IX	JOHN LIK
E IX IX IX 30: JOHN *MARY *MARY *SHOOT	JOHN LIK
E IX IX IX	MADY VEC
36: MARY *WHO *GIRL *GIVE2 *MARY *MARY ETABLE KNOW IX LIKE CORN1	MARY VEG
40: JOHN *VISIT *CORN *JOHN *MARY THINK MARY LOVE	JOHN IX
43: JOHN *PAST BUY HOUSE T BUY HOUSE	JOHN MUS
50: *JOHN JOHN BUY CAR SHOULD	FUTURE J
OHN BUY CAR SHOULD 54: JOHN *JOHN NOT BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE 57: JOHN *VEGETABLE VISIT MARY	JOHN DEC
IDE VISIT MARY 67: JOHN *JOHN NOT BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	
71: JOHN *GIVE1 *GO MARY L VISIT MARY	JOHN WIL
74: JOHN *WHO *MARY *SHOOT VISIT MARY	JOHN NOT
77: *JOHN BLAME MARY	ANN BLAM

E MARY	
84: *LOVE *NEW *HOMEWORK BOOK	IX-1P FI
ND SOMETHING-ONE BOOK 89: JOHN IX GIVE *MOTHER *GIVE NEW COAT	JOHN IX
GIVE MAN IX NEW COAT 90: JOHN *GIVE1 *GIVE1 SOMETHING-ONE WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	JOHN CTV
92: JOHN GIVE *SOMETHING-ONE SOMETHING-ONE WOMAN BOOK E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
100: POSS NEW CAR BREAK-DOWN CAR BREAK-DOWN	POSS NEW
105: JOHN *VEGETABLE	JOHN LEG
107: JOHN *SUE FRIEND *GO *WHO S FRIEND HAVE CANDY	JOHN POS
108: WOMAN *BOOK	WOMAN AR
RIVE	WOHAN AN
113: *JOHN CAR BLUE *JOHN *BUY1 LUE SUE BUY	IX CAR B
119: *JOHN *BUY1 *SUE *TOY *JANA	SUE BUY
IX CAR BLUE 122: JOHN *HOUSE BOOK	JOHN REA
D BOOK	JOHN KLA
139: JOHN *BUY1 WHAT YESTERDAY BOOK	JOHN BUY
WHAT YESTERDAY BOOK	
142: JOHN BUY YESTERDAY *MANY BOOK	JOHN BUY
YESTERDAY WHAT BOOK 158: LOVE *SOMETHING-ONE WHO	LOVE JOH
N WHO	
167: JOHN *TOY1 *MARY LOVE *LOVE	JOHN IX
SAY LOVE MARY 171: *MARY *JOHN BLAME	JOHN MAR
Y BLAME	JUNIN MAK
174: *GIVE1 GROUP GIVE1 *CORN TOY	PEOPLE G
ROUP GIVE1 JANA TOY	
181: *SUE *BOX	JOHN ARR
IVE	ALL DOV
184: ALL BOY *SELL TEACHER *CORN GIVE TEACHER APPLE	ALL BOY
189: JOHN *JANA *CORN *BUY1	JOHN GIV
E GIRL BOX	
193: JOHN *GIVE1 *CORN BOX E GIRL BOX	JOHN GIV
199: *JOHN CHOCOLATE *FRANK	LIKE CHO
COLATE WHO	JOHN TEI
201: JOHN *SHOULD *WOMAN *LIKE 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-polar-norm-rtheta', '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-lr', 'delta-norm-polar-ltheta', 'del	lar-rr', olar-rr',
**** WER = 0.46629213483146065	
Total correct: 95 out of 178	
Video Recognized	Correct
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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
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	JOHN NOT ANN BLAM IX-1P FI JOHN IX
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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
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	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 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 *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 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 ROUP GIVE1 JANA TOY	PEOPLE G
181: *SUE ARRIVE IVE	JOHN ARR
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	JOHN GIV
199: *JOHN CHOCOLATE WHO COLATE WHO	LIKE CHO
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-polar-lr', 'delta-norm-polar-ltheta' s 'my_model_selectors.SelectorBIC'>	lar-rr', olar-rr',
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*** UED 0 43505530343403445	
**** WER = 0.42696629213483145 Total correct: 102 out of 178	
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Total correct: 102 out of 178 Video Recognized ===================================	JOHN WRI JOHN CAN JOHN CAN JOHN FIS JOHN LIK JOHN LIK
Total correct: 102 out of 178 Video Recognized	JOHN WRI JOHN CAN JOHN FIS JOHN LIK JOHN LIK JOHN LIK MARY VEG
Total correct: 102 out of 178 Video Recognized ===================================	JOHN WRI JOHN CAN JOHN FIS JOHN LIK JOHN LIK JOHN LIK MARY VEG JOHN IX
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Total correct: 102 out of 178 Video Recognized	JOHN WRI JOHN CAN JOHN FIS JOHN LIK JOHN LIK JOHN LIK MARY VEG JOHN IX

57: JOHN *JOHN *IX *GIVE	JOHN DEC
IDE VISIT MARY 67: JOHN FUTURE NOT BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	301
71: JOHN *FUTURE VISIT MARY	JOHN WIL
L VISIT MARY	
74: JOHN *MARY *MARY MARY	JOHN NOT
VISIT MARY	ANINI DI AM
77: *JOHN BLAME MARY E MARY	ANN BLAM
84: *JOHN *NEW *YESTERDAY *NEW	IX-1P FI
ND SOMETHING-ONE BOOK	
89: JOHN IX GIVE *THROW IX NEW COAT	JOHN IX
GIVE MAN IX NEW COAT	
90: JOHN *IX IX *IX WOMAN BOOK	JOHN GIV
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92: JOHN *WOMAN IX *IX WOMAN BOOK	JOHN GIV
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100: POSS NEW CAR BREAK-DOWN CAR BREAK-DOWN	POSS NEW
105: JOHN *VEGETABLE	JOHN LEG
107: JOHN *IX FRIEND *MARY *JOHN	JOHN POS
S FRIEND HAVE CANDY	301
108: WOMAN ARRIVE	WOMAN AR
RIVE	
113: *JOHN CAR *JOHN *JOHN *BUY1	IX CAR B
LUE SUE BUY	
119: *JOHN *BUY1 IX CAR *JANA	SUE BUY
IX CAR BLUE 122: JOHN READ *COAT	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 JOHN WHO	LOVE JOH
N WHO	
167: JOHN *JOHN LOVE MARY	JOHN IX
SAY LOVE MARY 171: *MARY *JOHN BLAME	JOHN MAR
Y BLAME	JOHN MAIN
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	JOHN CTV
189: JOHN *JOHN BOX E GIRL BOX	JOHN GIV
193: JOHN *IX *CORN BOX	JOHN GIV
E GIRL BOX	301 011
199: *JOHN CHOCOLATE WHO	LIKE CHO
COLATE WHO	
201: JOHN *JOHN MARY *JOHN BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	
running: ['dist-norm-left-right', 'delta-dist-norm-left-right',	
rm-rx', 'delta-norm-ry', 'delta-norm-lx', 'delta-norm-ly', 'norm-po	tan-un'

'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
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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 LUE SUE BUY	IX CAR B
119: *JOHN *BUY1 IX CAR *IX IX CAR BLUE	SUE BUY
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 YESTERDAY WHAT BOOK	JOHN BUY
158: LOVE JOHN WHO N WHO	LOVE JOH
167: JOHN *JOHN *JOHN LOVE MARY SAY LOVE MARY	JOHN IX
171: *MARY *JOHN BLAME Y BLAME	JOHN MAR
174: *CAR GROUP GIVE1 *JOHN *WHAT ROUP GIVE1 JANA TOY	PEOPLE G
181: *SUE ARRIVE IVE	JOHN ARR
184: ALL BOY *GIVE1 TEACHER APPLE GIVE TEACHER APPLE	ALL BOY
189: JOHN *JOHN *JOHN *WHAT E GIRL BOX	JOHN GIV
193: JOHN *POSS *CORN BOX E GIRL BOX	JOHN GIV
199: *JOHN CHOCOLATE *MARY COLATE WHO	LIKE CHO
201: JOHN *JOHN MARY *JOHN BUY HOUSE L MARY IX-1P BUY HOUSE Pupping: ['dist norm left night' 'delta dist norm left night'	JOHN TEL
<pre>running: ['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'></pre>	ar-rr', lar-rr',
**** WER = 0.46629213483146065 Total correct: 95 out of 178	
Video Recognized	Correct
2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK 7: JOHN *TOY *HAVE CAN	JOHN CAN
GO CAN 12: JOHN *CAR *GO1 CAN GO CAN	JOHN CAN
21: JOHN *JOHN WONT *MARY *CAR *CAR *FUTURE *MARY H WONT EAT BUT CAN EAT CHICKEN	JOHN FIS
25: JOHN *IX IX IX IX E IX IX IX	JOHN LIK
28: JOHN *WHO IX IX IX E IX IX IX	JOHN LIK
30: JOHN *MARY *MARY *SHOOT E IX IX	JOHN LIK
36: MARY *JOHN *WOMAN *GIVE2 *MARY *MARY	MARY VEG

ETABLE KNOW IX LIKE CORN1	
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43: JOHN *POSS BUY HOUSE	JOHN MUS
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57: JOHN *JOHN VISIT *WOMAN	JOHN DEC
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L VISIT MARY	JOHN WIL
74: JOHN *MARY *MARY MARY	JOHN NOT
VISIT MARY	
77: *JOHN *ARRIVE MARY	ANN BLAM
E MARY	
84: *JOHN *NEW *YESTERDAY BOOK	IX-1P FI
ND SOMETHING-ONE BOOK 89: JOHN IX *IX *THINK IX NEW *BOOK	JOHN IX
GIVE MAN IX NEW COAT	JOHN IX
90: JOHN *WOMAN *GIVE *WOMAN WOMAN *LOVE	JOHN GIV
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92: JOHN *IX IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	DOCC NEW
100: POSS NEW CAR BREAK-DOWN CAR BREAK-DOWN	POSS NEW
105: JOHN *VEGETABLE	JOHN LEG
	JOHN LEG JOHN POS
105: JOHN *VEGETABLE	JOHN POS
105: JOHN *VEGETABLE 107: JOHN *JOHN FRIEND HAVE *MARY S FRIEND HAVE CANDY 108: *MARY ARRIVE	
105: JOHN *VEGETABLE 107: JOHN *JOHN FRIEND HAVE *MARY S FRIEND HAVE CANDY 108: *MARY ARRIVE RIVE	JOHN POS WOMAN AR
105: JOHN *VEGETABLE 107: JOHN *JOHN FRIEND HAVE *MARY S FRIEND HAVE CANDY 108: *MARY ARRIVE RIVE 113: *JOHN *TOY *JOHN *MARY *BUY1	JOHN POS
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105: JOHN *VEGETABLE 107: JOHN *JOHN FRIEND HAVE *MARY S FRIEND HAVE CANDY 108: *MARY ARRIVE RIVE 113: *JOHN *TOY *JOHN *MARY *BUY1 LUE SUE BUY 119: *JOHN *BUY1 *HAVE *HAVE *VISIT IX CAR BLUE 122: JOHN *GO BOOK D BOOK	JOHN POS WOMAN AR IX CAR B SUE BUY JOHN REA
105: JOHN *VEGETABLE 107: JOHN *JOHN FRIEND HAVE *MARY S FRIEND HAVE CANDY 108: *MARY ARRIVE RIVE 113: *JOHN *TOY *JOHN *MARY *BUY1 LUE SUE BUY 119: *JOHN *BUY1 *HAVE *HAVE *VISIT IX CAR BLUE 122: JOHN *GO BOOK D BOOK 139: JOHN *BUY1 WHAT *SOMETHING-ONE *ARRIVE	JOHN POS WOMAN AR IX CAR B SUE BUY
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105: JOHN *VEGETABLE 107: JOHN *JOHN FRIEND HAVE *MARY S FRIEND HAVE CANDY 108: *MARY ARRIVE RIVE 113: *JOHN *TOY *JOHN *MARY *BUY1 LUE SUE BUY 119: *JOHN *BUY1 *HAVE *HAVE *VISIT IX CAR BLUE 122: JOHN *GO BOOK D BOOK 139: JOHN *BUY1 WHAT *SOMETHING-ONE *ARRIVE WHAT YESTERDAY BOOK 142: JOHN BUY YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK 158: LOVE JOHN WHO N WHO 167: JOHN *JOHN *SAY-1P LOVE MARY SAY LOVE MARY 171: *MARY *JOHN BLAME	JOHN POS WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY JOHN BUY LOVE JOH
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105: JOHN *VEGETABLE 107: JOHN *JOHN FRIEND HAVE *MARY S FRIEND HAVE CANDY 108: *MARY ARRIVE RIVE 113: *JOHN *TOY *JOHN *MARY *BUY1 LUE SUE BUY 119: *JOHN *BUY1 *HAVE *HAVE *VISIT IX CAR BLUE 122: JOHN *GO BOOK D BOOK 139: JOHN *BUY1 WHAT *SOMETHING-ONE *ARRIVE WHAT YESTERDAY BOOK 142: JOHN BUY YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK 158: LOVE JOHN WHO N WHO 167: JOHN *JOHN *SAY-1P LOVE MARY SAY LOVE MARY 171: *MARY *JOHN BLAME Y BLAME 174: *CAN GROUP GIVE1 *JOHN TOY ROUP GIVE1 JANA TOY 181: *SUE ARRIVE	JOHN POS WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY LOVE JOH JOHN IX JOHN MAR
105: JOHN *VEGETABLE 107: JOHN *JOHN FRIEND HAVE *MARY S FRIEND HAVE CANDY 108: *MARY ARRIVE RIVE 113: *JOHN *TOY *JOHN *MARY *BUY1 LUE SUE BUY 119: *JOHN *BUY1 *HAVE *HAVE *VISIT IX CAR BLUE 122: JOHN *GO BOOK D BOOK 139: JOHN *BUY1 WHAT *SOMETHING-ONE *ARRIVE WHAT YESTERDAY BOOK 142: JOHN BUY YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK 158: LOVE JOHN WHO N WHO 167: JOHN *JOHN *SAY-1P LOVE MARY SAY LOVE MARY 171: *MARY *JOHN BLAME Y BLAME 174: *CAN GROUP GIVE1 *JOHN TOY ROUP GIVE1 JANA TOY 181: *SUE ARRIVE IVE	JOHN POS WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY LOVE JOH JOHN IX JOHN MAR PEOPLE G JOHN ARR
105: JOHN *VEGETABLE 107: JOHN *JOHN FRIEND HAVE *MARY S FRIEND HAVE CANDY 108: *MARY ARRIVE RIVE 113: *JOHN *TOY *JOHN *MARY *BUY1 LUE SUE BUY 119: *JOHN *BUY1 *HAVE *HAVE *VISIT IX CAR BLUE 122: JOHN *GO BOOK D BOOK 139: JOHN *BUY1 WHAT *SOMETHING-ONE *ARRIVE WHAT YESTERDAY BOOK 142: JOHN BUY YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK 158: LOVE JOHN WHO N WHO 167: JOHN *JOHN *SAY-1P LOVE MARY SAY LOVE MARY 171: *MARY *JOHN BLAME Y BLAME 174: *CAN GROUP GIVE1 *JOHN TOY ROUP GIVE1 JANA TOY 181: *SUE ARRIVE IVE 184: *GIVE BOY *CAR TEACHER APPLE	JOHN POS WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY LOVE JOH JOHN IX JOHN MAR PEOPLE G
105: JOHN *VEGETABLE 107: JOHN *JOHN FRIEND HAVE *MARY S FRIEND HAVE CANDY 108: *MARY ARRIVE RIVE 113: *JOHN *TOY *JOHN *MARY *BUY1 LUE SUE BUY 119: *JOHN *BUY1 *HAVE *HAVE *VISIT IX CAR BLUE 122: JOHN *GO BOOK D BOOK 139: JOHN *BUY1 WHAT *SOMETHING-ONE *ARRIVE WHAT YESTERDAY BOOK 142: JOHN BUY YESTERDAY WHAT BOOK YESTERDAY WHAT BOOK 158: LOVE JOHN WHO N WHO 167: JOHN *JOHN *SAY-1P LOVE MARY SAY LOVE MARY 171: *MARY *JOHN BLAME Y BLAME 174: *CAN GROUP GIVE1 *JOHN TOY ROUP GIVE1 JANA TOY 181: *SUE ARRIVE IVE	JOHN POS WOMAN AR IX CAR B SUE BUY JOHN REA JOHN BUY LOVE JOH JOHN IX JOHN MAR PEOPLE G JOHN ARR

E GIRL BOX 193: JOHN *GIVE1 GIRL BOX JOHN GIV E GIRL BOX 199: *JOHN CHOCOLATE *MARY LIKE CHO COLATE WHO 201: JOHN *SHOULD *LOVE *LIKE 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
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 CAR BREAK-DOWN	POSS NEW
105: JOHN *SEE	JOHN LEG
107: JOHN *IX *CAR HAVE *JOHN	JOHN POS
S FRIEND HAVE CANDY 108: *LOVE *BOOK	WOMAN AR
RIVE	
113: *JOHN CAR *JOHN *JOHN *BUY1	IX CAR B
LUE SUE BUY 119: *WHO *BUY1 IX CAR *JOHN	SUE BUY
IX CAR BLUE	302 301
122: JOHN *GIVE1 BOOK	JOHN REA
D BOOK	70.00
139: JOHN *BUY1 WHAT YESTERDAY BOOK WHAT YESTERDAY BOOK	JOHN BUY
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	301 201
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	JOHN MAR
174: *CAR *GIVE1 GIVE1 *WHO *CAN	PEOPLE G
ROUP GIVE1 JANA TOY	
181: JOHN *BOX	JOHN ARR
IVE	ALL DOV
184: *IX BOY *GIVE1 TEACHER APPLE GIVE TEACHER APPLE	ALL BOY
189: JOHN *SEE GIRL *CAR	JOHN GIV
E GIRL BOX	
193: JOHN *SEE GIRL BOX	JOHN GIV
E GIRL BOX	
199: *JOHN CHOCOLATE *MARY COLATE WHO	LIKE CHO
201: JOHN *THINK *WOMAN *LIKE BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	301 122
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-polar 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 nr-lr', 'n a-norm-po</td></class>	'delta-n nr-lr', 'n a-norm-po
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Total correct: 98 out of 178	
Video Recognized	Correct
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2 70/W UDITE HOMEHODY	70171 1:55
2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK 7: JOHN *CAR GO CAN	JOHN CAN
GO CAN	JOIN CAN
12: JOHN CAN *GO1 CAN	JOHN CAN

GO CAN 21: JOHN *NEW *VISIT *JOHN *CAR *CAR *FUTURE *FUTURE	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	301111 1 13
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36: MARY *JOHN *GIRL *VISIT *JOHN *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1	
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OHN BUY CAR SHOULD	1010112 3
54: JOHN SHOULD *FUTURE BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	
57: *IX *JOHN *IX *IX	JOHN DEC
IDE VISIT MARY	JOHN FUT
67: JOHN FUTURE NOT BUY HOUSE URE NOT BUY HOUSE	JOHN FUT
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 84: *JOHN *NEW *HOMEWORK BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	1/1 11
89: JOHN *POSS *MAN MAN IX NEW COAT	JOHN IX
GIVE MAN IX NEW COAT	
90: JOHN *GIVE1 IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	701BL 671/
92: JOHN *MAN IX *IX WOMAN BOOK E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
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105: JOHN *SEE	JOHN LEG
107: *MARY *IX FRIEND *IX *JOHN	JOHN POS
S FRIEND HAVE CANDY	
108: *MARY *HOMEWORK	WOMAN AR
RIVE 113: IX CAR *JOHN *JOHN *BUY1	IX CAR B
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142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	55.11 561
158: LOVE JOHN WHO	LOVE JOH
N WHO	
167: JOHN IX *VISIT LOVE MARY	JOHN IX

CAV LOVE MARV	
SAY LOVE MARY 171: *MARY *JOHN BLAME Y BLAME	JOHN MAR
174: *CAR GROUP GIVE1 *JOHN TOY ROUP GIVE1 JANA TOY	PEOPLE G
181: JOHN *VIDEOTAPE TVF	JOHN ARR
184: ALL BOY *GIVE1 TEACHER APPLE GIVE TEACHER APPLE	ALL BOY
189: JOHN *JOHN *PREFER *CAN E GIRL BOX	JOHN GIV
193: JOHN *IX *YESTERDAY BOX E GIRL BOX	JOHN GIV
199: *JOHN CHOCOLATE *JOHN COLATE WHO	LIKE CHO
201: JOHN *GIVE1 *WOMAN *WOMAN BUY HOUSE L MARY IX-1P BUY HOUSE	JOHN TEL
running: ['norm-rx', 'norm-ry', 'norm-lx', 'norm-ly', 'dist-norm'nt', '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', 'delta-lar-lr', 'delta-norm-polar-ltheta'] <class 'my_model_selectors.selectors.<="" td=""><td>, 'delta-n ar-lr', 'n ta-norm-po</td></class>	, 'delta-n ar-lr', 'n ta-norm-po
**** WER = 0.4606741573033708	
Total correct: 96 out of 178 Video Recognized	Correct
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2: JOHN WRITE *ARRIVE TE HOMEWORK	JOHN WRI
TE HOMEWORK 7: JOHN *CAR GO CAN	JOHN WRI
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TE HOMEWORK 7: JOHN *CAR GO CAN GO CAN 12: JOHN CAN *GO1 CAN	JOHN CAN
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TE HOMEWORK 7: JOHN *CAR GO CAN GO CAN 12: JOHN CAN *GO1 CAN GO CAN 21: JOHN *JOHN *JOHN *JOHN *CAR *CAR *FUTURE *FUTURE H WONT EAT BUT CAN EAT CHICKEN 25: JOHN *IX *LOVE IX IX E IX IX IX 28: *ANN *IX IX IX IX E IX IX IX 30: *IX *MARY IX IX IX E IX IX IX 36: MARY *JOHN *GIVE3 *VISIT *JOHN *MARY ETABLE KNOW IX LIKE CORN1 40: JOHN IX *JOHN MARY *IX THINK MARY LOVE 43: JOHN *JOHN BUY HOUSE	JOHN CAN JOHN FIS JOHN LIK JOHN LIK MARY VEG JOHN IX
TE HOMEWORK 7: JOHN *CAR GO CAN GO CAN 12: JOHN CAN *GO1 CAN GO CAN 21: JOHN *JOHN *JOHN *JOHN *CAR *CAR *FUTURE *FUTURE H WONT EAT BUT CAN EAT CHICKEN 25: JOHN *IX *LOVE IX IX E IX IX IX 28: *ANN *IX IX IX IX E IX IX IX 30: *IX *MARY IX IX IX E IX IX IX 36: MARY *JOHN *GIVE3 *VISIT *JOHN *MARY ETABLE KNOW IX LIKE CORN1 40: JOHN IX *JOHN MARY *IX THINK MARY LOVE 43: JOHN *JOHN BUY HOUSE T BUY HOUSE 50: *JOHN *SEE BUY CAR *JOHN	JOHN CAN JOHN FIS JOHN LIK JOHN LIK MARY VEG JOHN IX JOHN MUS
TE HOMEWORK 7: JOHN *CAR GO CAN GO CAN 12: JOHN CAN *GO1 CAN GO CAN 21: JOHN *JOHN *JOHN *JOHN *CAR *CAR *FUTURE *FUTURE H WONT EAT BUT CAN EAT CHICKEN 25: JOHN *IX *LOVE IX IX E IX IX IX 28: *ANN *IX IX IX IX E IX IX IX 30: *IX *MARY IX IX IX E IX IX IX 36: MARY *JOHN *GIVE3 *VISIT *JOHN *MARY ETABLE KNOW IX LIKE CORN1 40: JOHN IX *JOHN MARY *IX THINK MARY LOVE 43: JOHN *JOHN BUY HOUSE T BUY HOUSE 50: *JOHN *SEE BUY CAR *JOHN OHN BUY CAR SHOULD 54: JOHN *FUTURE *FUTURE BUY HOUSE	JOHN CAN JOHN FIS JOHN LIK JOHN LIK JOHN LIK MARY VEG JOHN IX JOHN MUS FUTURE J
TE HOMEWORK 7: JOHN *CAR GO CAN GO CAN 12: JOHN CAN *GO1 CAN GO CAN 21: JOHN *JOHN *JOHN *JOHN *CAR *CAR *FUTURE *FUTURE H WONT EAT BUT CAN EAT CHICKEN 25: JOHN *IX *LOVE IX IX E IX IX IX 28: *ANN *IX IX IX IX E IX IX IX 30: *IX *MARY IX IX IX E IX IX IX 36: MARY *JOHN *GIVE3 *VISIT *JOHN *MARY ETABLE KNOW IX LIKE CORN1 40: JOHN IX *JOHN MARY *IX THINK MARY LOVE 43: JOHN *JOHN BUY HOUSE T BUY HOUSE 50: *JOHN *SEE BUY CAR *JOHN OHN BUY CAR SHOULD 54: JOHN *FUTURE *FUTURE BUY HOUSE ULD NOT BUY HOUSE 57: *IX *MARY VISIT *IX	JOHN CAN JOHN FIS JOHN LIK JOHN LIK JOHN LIK MARY VEG JOHN IX JOHN MUS FUTURE J JOHN SHO

L VISIT MARY	
74: *IX *MARY *MARY MARY	JOHN NOT
VISIT MARY	
77: *JOHN BLAME MARY	ANN BLAM
E MARY	
84: *JOHN *ARRIVE *CAR BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	701N TV
89: JOHN IX *IX *IX NEW COAT	JOHN IX
GIVE MAN IX NEW COAT 90: *MARY *GIVE1 IX *IX WOMAN BOOK	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	30 011
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	
113: IX CAR *JOHN *JOHN *BUY1	IX CAR B
LUE SUE BUY	CHE DIN
119: *MARY *BUY1 IX *JOHN *IX	SUE BUY
IX CAR BLUE 122: JOHN *HOUSE BOOK	JOHN REA
D BOOK	JUHN KEA
139: *IX *BUY1 WHAT YESTERDAY BOOK	JOHN BUY
WHAT YESTERDAY BOOK	301 201
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	
171: *MARY *JOHN BLAME	JOHN MAR
Y BLAME	DE001 E 6
174: *JOHN *GIVE1 GIVE1 *JOHN TOY	PEOPLE G
ROUP GIVE1 JANA TOY 181: JOHN ARRIVE	JOHN ARR
IVE	JOHN ANN
184: *IX BOY *GIVE1 TEACHER APPLE	ALL BOY
GIVE TEACHER APPLE	,,,,,,
189: JOHN *MARY *PREFER BOX	JOHN GIV
E GIRL BOX	
193: JOHN *POSS *VISIT BOX	JOHN GIV
E GIRL BOX	
199: *JOHN *ARRIVE WHO	LIKE CHO
COLATE WHO	
201: JOHN *GIVE1 *IX *LIKE BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSErunning: ['norm-rx', 'norm-ry', 'norm-lx', 'norm-ly', 'dist-norm	-lof+ =:-
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', 'delt	
lar-lr', 'delta-norm-polar-ltheta'] <class 'my_model_selectors.selectors<="" td=""><td></td></class>	

Video Recognized	Correct
2: JOHN WRITE HOMEWORK	JOHN WRI
TE HOMEWORK	
7: JOHN *PEOPLE *HAVE CAN	JOHN CAN
GO CAN	
12: JOHN *CAR *GO1 CAN	JOHN CAN
GO CAN 21: JOHN *HOMEWORK *HOMEWORK *MARY *CAR *CAR *FUTURE *MARY	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	301114 1 13
25: *ANN *ANN *ANN *LIKE *ANN	JOHN LIK
E IX IX IX	
28: JOHN LIKE *ANN *ANN IX	JOHN LIK
E IX IX IX	JOHN LTV
30: JOHN *MARY *MARY *MARY *SHOOT E IX IX IX	JOHN LIK
36: MARY *JOHN *YESTERDAY *SHOOT LIKE *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1	
40: JOHN *MARY *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	FUTURE J
54: JOHN *JOHN NOT BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	
57: JOHN *MARY VISIT MARY	JOHN DEC
IDE VISIT MARY	
67: JOHN *POSS NOT BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE 71: JOHN *JOHN VISIT MARY	JOHN WIL
L VISIT MARY	JOHN WIL
74: JOHN *MARY *MARY MARY	JOHN NOT
VISIT MARY	
77: *JOHN BLAME MARY	ANN BLAM
E MARY	TV 1D FT
84: *GO *ARRIVE *HOMEWORK BOOK ND SOMETHING-ONE BOOK	IX-1P FI
89: JOHN IX *IX *GO IX NEW COAT	JOHN IX
GIVE MAN IX NEW COAT	
90: JOHN *GIVE1 IX *GIVE1 WOMAN *VIDEOTAPE	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	POSS NEW
105: JOHN *POSS	JOHN LEG
107: JOHN *JOHN *HAVE HAVE *MARY	JOHN POS
S FRIEND HAVE CANDY	
108: *LOVE ARRIVE	WOMAN AR
RIVE	TV CAR R
113: *JOHN CAR *MARY *JOHN *BUY1 LUE SUE BUY	IX CAR B
119: *WHO *BUY1 *GO CAR *VISIT	SUE BUY
IX CAR BLUE	
In the second	

122: JOHN *BLAME BOOK	JOHN REA
D BOOK 139: JOHN *BUY1 WHAT YESTERDAY *VIDEOTAPE WHAT YESTERDAY BOOK	JOHN BUY
142: JOHN BUY YESTERDAY WHAT BOOK	JOHN BUY
YESTERDAY WHAT BOOK	
158: LOVE *MARY *MARY	LOVE JOH
N WHO	
167: JOHN *JOHN *VISIT LOVE MARY	JOHN IX
SAY LOVE MARY	
171: *MARY *JOHN BLAME	JOHN MAR
Y BLAME	
174: *CAR GROUP GIVE1 *WHO TOY	PEOPLE G
ROUP GIVE1 JANA TOY	
181: *SOMETHING-ONE *BOX	JOHN ARR
IVE	
184: *IX BOY *GIVE1 TEACHER APPLE	ALL BOY
GIVE TEACHER APPLE	
189: JOHN *GIVE1 *JOHN BOX	JOHN GIV
E GIRL BOX	
193: JOHN *SEE *NOT BOX	JOHN GIV
E GIRL BOX	
199: *JOHN CHOCOLATE *MARY	LIKE CHO
COLATE WHO	
201: JOHN *WHO *WOMAN *WOMAN BUY HOUSE	JOHN TEL
L MARY IX-1P BUY HOUSE	

best 5:

	Features	Selector	WER	Num correct of 178
26	features_norm_polar_coords	SelectorDIC	0.404494	106
29	features_custom	SelectorBIC	0.426966	102
25	features_norm_polar_coords	SelectorBIC	0.426966	102
27	features_norm_polar_coords	SelectorCV	0.449438	98
33	features_best	SelectorBIC	0.449438	98

worst 5:

	Features	Selector	WER	Num correct of 178
16	features_hand_dist	SelectorConstant	0.865169	24
18	features_hand_dist	SelectorDIC	0.837079	29
19	features_hand_dist	SelectorCV	0.808989	34
17	features_hand_dist	SelectorBIC	0.808989	34
7	features_norm	SelectorCV	0.679775	57

Out[185]: Selector

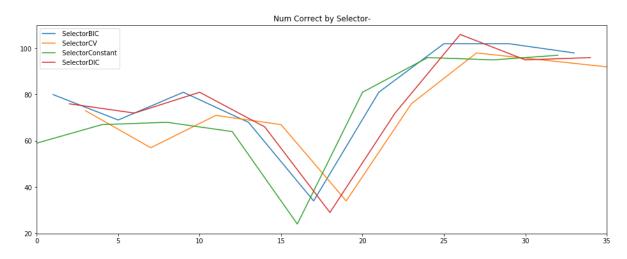
 SelectorBIC
 Axes(0.125,0.125;0.775x0.755)

 SelectorCV
 Axes(0.125,0.125;0.775x0.755)

 SelectorConstant
 Axes(0.125,0.125;0.775x0.755)

 SelectorDIC
 Axes(0.125,0.125;0.775x0.755)

Name: Num correct of 178, dtype: object

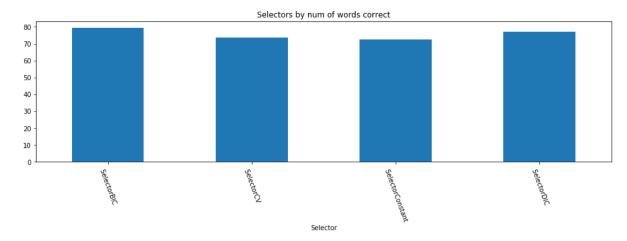


Selectors ordered by best

Selector

SelectorBIC 0.553683
SelectorDIC 0.567416
SelectorCV 0.586142
SelectorConstant 0.593633
Name: WER, dtype: float64

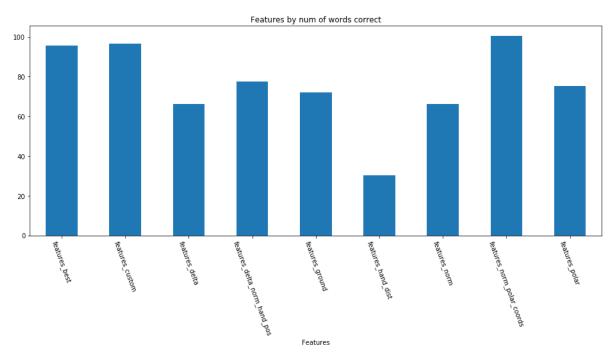
Out[213]: <matplotlib.axes._subplots.AxesSubplot at 0x1bff04cc208>



Features ordered by best

Features	
features_norm_polar_coords	0.435393
features_custom	0.456461
features_best	0.462079
<pre>features_delta_norm_hand_pos</pre>	0.564607
features_polar	0.577247
features_ground	0.595506
features_delta	0.627809
features_norm	0.627809
features_hand_dist	0.830056
Name: WER, dtype: float64	

Out[214]: <matplotlib.axes._subplots.AxesSubplot at 0x1bff08a8518>



In [215]: # 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 12: JOHN CAN *GO1 CAN	JOHN CAN
GO CAN	JOHN CAN
21: JOHN *VIDEOTAPE WONT *WHO BUT *CAR *FUTURE *MARY	JOHN FIS
H WONT EAT BUT CAN EAT CHICKEN	
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	JOHN LIK
36: MARY *JOHN *GIRL *GIVE *MARY *MARY	MARY VEG
ETABLE KNOW IX LIKE CORN1	
40: JOHN *GIVE *CORN MARY *MARY	JOHN IX
THINK MARY LOVE	
43: JOHN *POSS BUY HOUSE	JOHN MUS
T BUY HOUSE	FUTURE 3
50: *JOHN JOHN BUY CAR *MARY OHN BUY CAR SHOULD	FUTURE J
54: JOHN *FUTURE *FUTURE BUY HOUSE	JOHN SHO
ULD NOT BUY HOUSE	301111 3110
57: *MARY *JOHN VISIT MARY	JOHN DEC
IDE VISIT MARY	
67: JOHN FUTURE NOT BUY HOUSE	JOHN FUT
URE NOT BUY HOUSE	70.00
71: JOHN *FUTURE VISIT MARY L VISIT MARY	JOHN WIL
74: JOHN *MARY *MARY MARY	JOHN NOT
VISIT MARY	JOHN NOT
77: *JOHN BLAME MARY	ANN BLAM
E MARY	
84: *JOHN *BUY *HOMEWORK BOOK	IX-1P FI
ND SOMETHING-ONE BOOK	
89: JOHN *JOHN *WOMAN *THROW IX *BUY COAT	JOHN IX
GIVE MAN IX NEW COAT 90: JOHN *IX IX *IX WOMAN BOOK	JOHN GIV
E IX SOMETHING-ONE WOMAN BOOK	JOHN GIV
92: JOHN GIVE *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	JOHN POS
S FRIEND HAVE CANDY 108: *JOHN *BOOK	WOMAN AR
RIVE	WOMAN AR
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 LIWIT IV-IL 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 = 0.0.404494, 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 SelectorConstant, with a WER = 0.865169 and Total correct: 24 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 = 0.393258, and Total correct: 108 out of 178.

This validates the idea that normalized data/polar coordinates/hand-distance features are the most valuablefeatures, and the original data needs to be greatly transformed to be most useful.

From the data collected by running all the selectors and features, we can see that the BIC selector and the features_norm_polar_coords actually had the best overall scores.

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 stackin g 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 statistical language models (SLM) (https://en.wikipedia.org/wiki/Language_model). 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