

# CE Diary Autocoder Demo

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# What is Machine Learning?

- Definition: Machine learning is programming computers to **optimize a performance criterion** using example data or **past experience**
- Goal: Build a model that is a **good and useful approximation** to the data

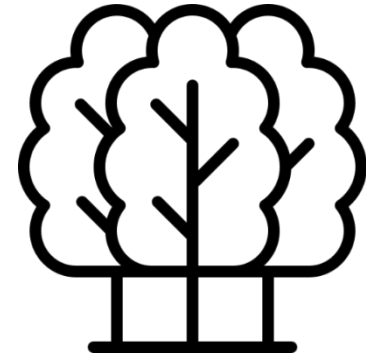
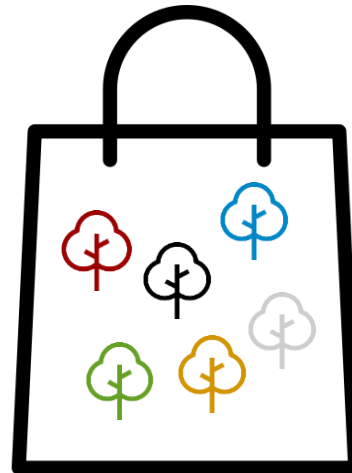
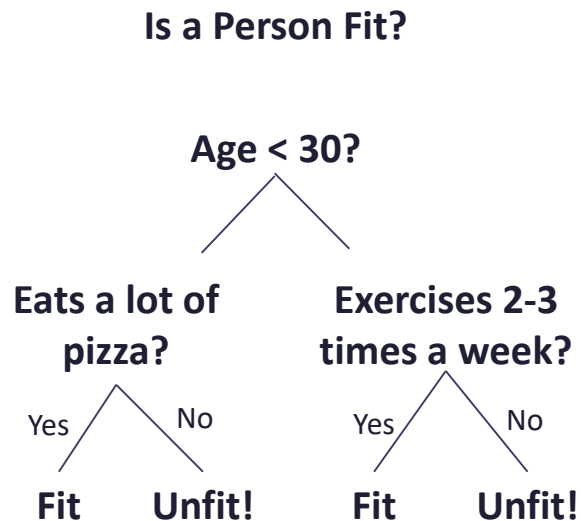
## Machine Learning is Like Gardening



# What is a Random Forest Model?

Random forest models are **bagged decision tree** models that split on a **subset of features** at each split.

## Decision Tree:



# Motivation

The Bureau of Labor Statistics wants to automatically assign item codes in the Diary survey.

The process is currently labor intensive and expensive.

The existing autocoder is a rule based system that needs to account for special cases, which leads to inaccuracies.

Creating a new autocoder using machine learning can: **reduce costs, improve accuracy.**

# Contributions

## Models

Four Models: ECLO, EFDB, EOTH, EMLS

## Data and Analysis

Spell Checker created using Levenshtein, Jaro Winkler and QWERTY distance

Module for analyzing Unclassifiable diary items

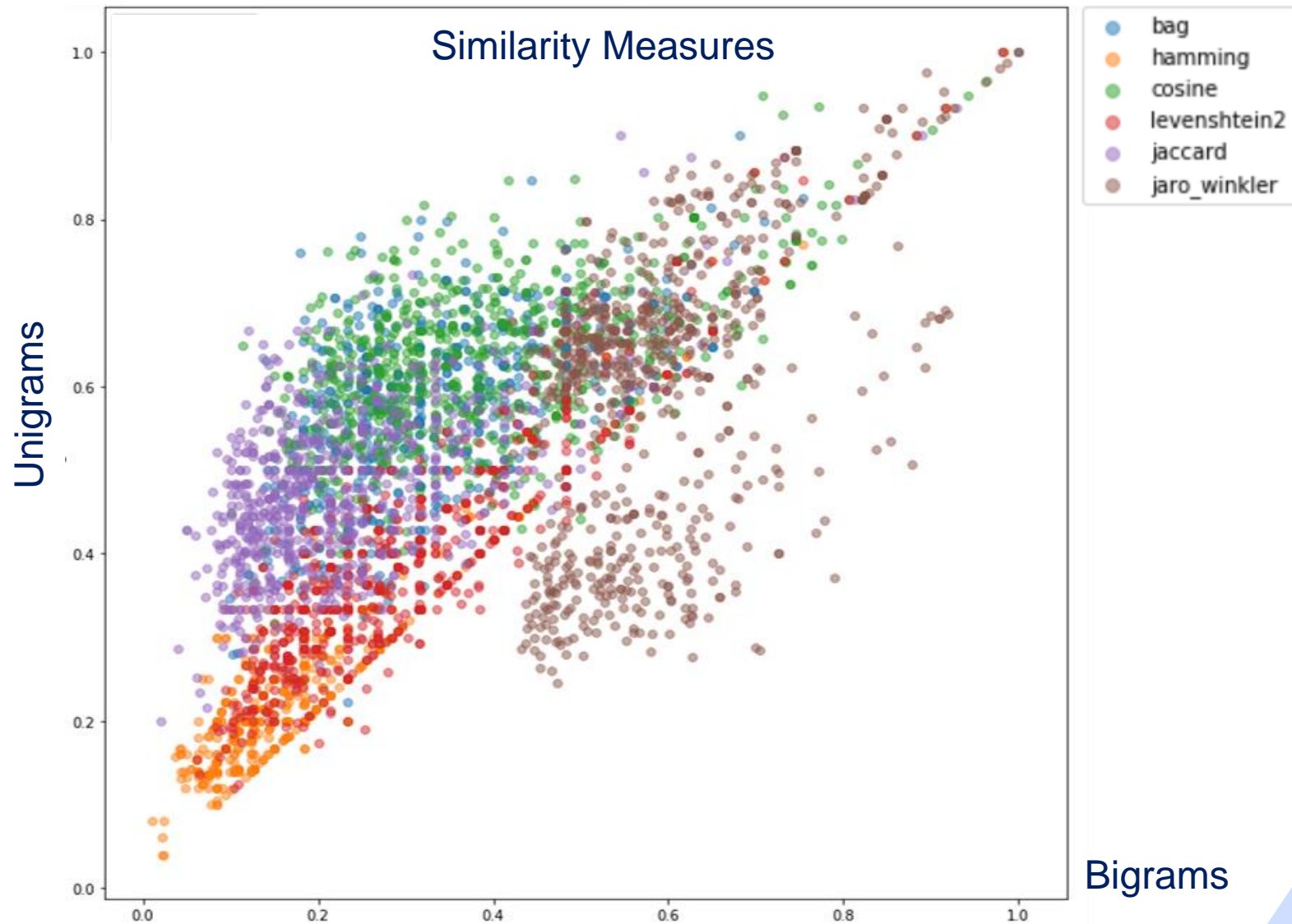
Analytics Dashboard UI using Dash

# Data Exploration



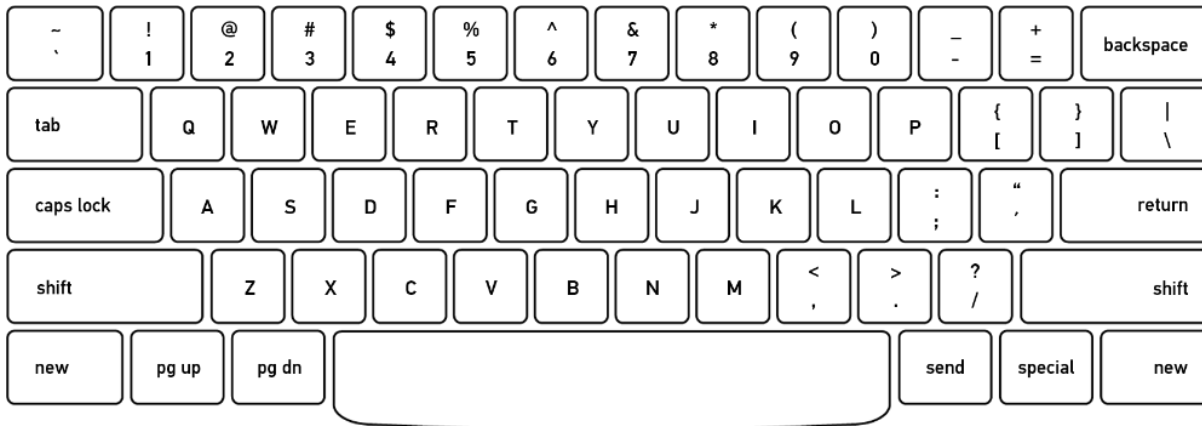
**Total: 753**  
(not including >900000)

# Dealing with Dirty Data



# Spell Checker

LABOT vs LAOBR to LABOR



Transposition/Replace  
QWERTY Penalty:  
T -> R =  $\log(1)$   
B <-> O =  $\log(4)$

```
1 {  
2   "spagh": "spaghetti",  
3   "spagheti": "spaghetti",  
4   "spaghettie": "spaghetti",  
5   "spaghtti": "spaghetti",  
6 }
```

Insertion/Deletion  
Penalty: 1

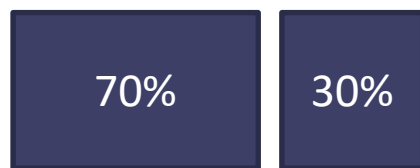
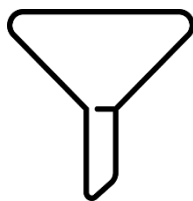


# Model Architecture

Item Descriptions are **spell checked and vectorized** before being split into training and testing data sets.

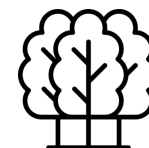
The data sets are then fed into respective Random Forest Models and **Item predictions are reflected on the dashboard.**

3 Years of SAS Data



Train

Test



Spell checked

TfidfVectorizer ngrams = (2,3)

shirt: sh, hi, ir, rt, shi, hir, irt

i.e.:

n\_estimators = 200

max\_depth = 100

criterion = entropy

# Train Model

Each RF model is trained using KFold cross validation.

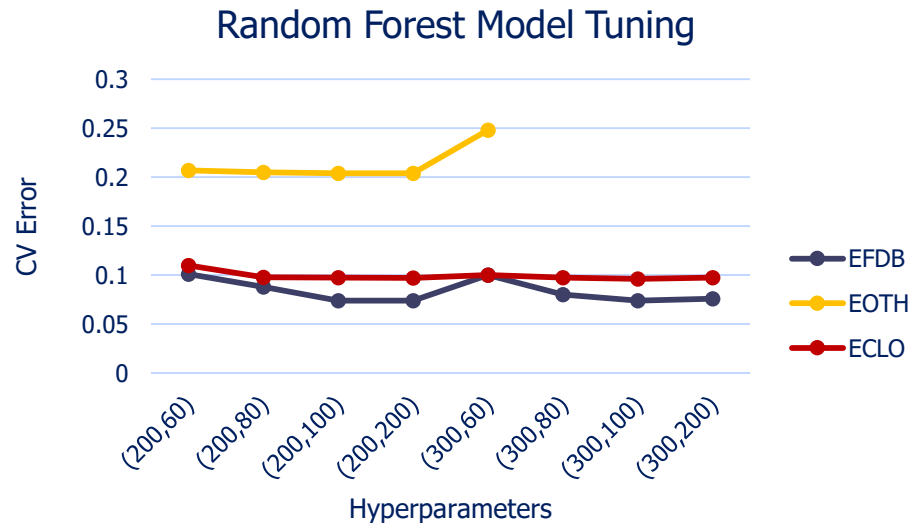
Hyperparameter settings:

n\_estimators: [200, 300]  
max\_depth: [60, 80, 100, 200]  
criterion: ['gini', 'entropy']

Total # of features

Other models tried:

Logistic Regression, SVM, Decision Tree



# Demo

- Installation:
  - ▶ Anaconda/Python required
  - ▶ Pip install autocoder package
- Dashboard
- Download to Excel

```
Anaconda Prompt - python upload_component.py

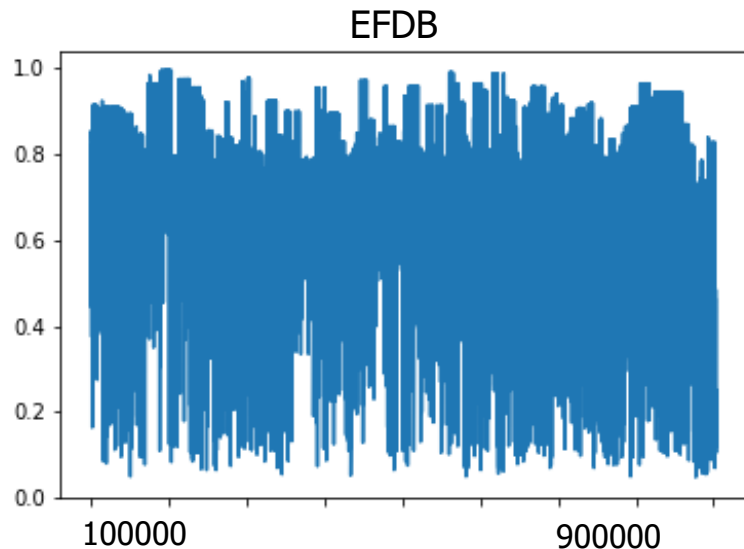
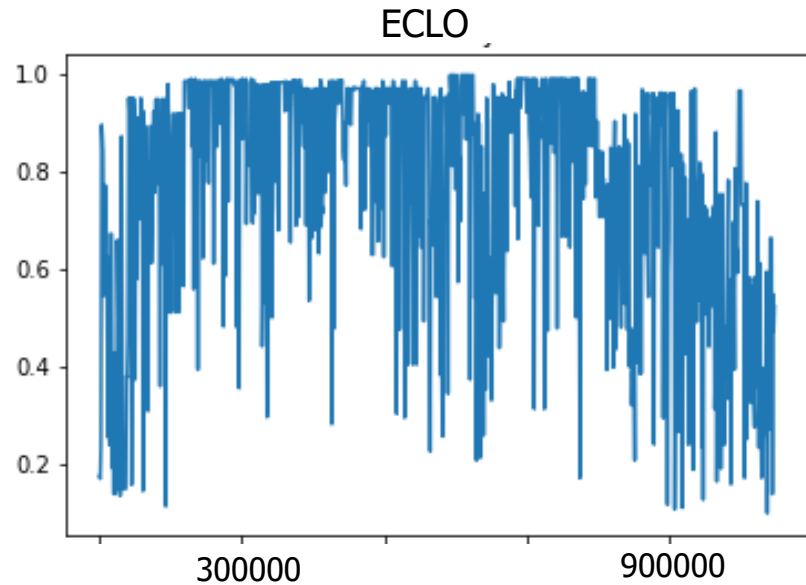
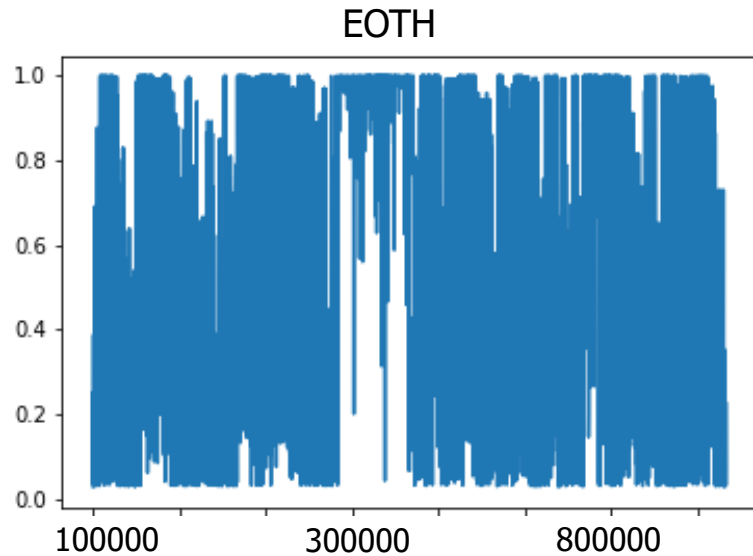
(base) C:\>cd C:\Users\li_m\Documents\autocode\DiaryAutocoding\front

(base) C:\Users\li_m\Documents\autocode\DiaryAutocoding\front>python upload_component.py
Running on http://127.0.0.1:8050/
Debugger PIN: 770-477-768
* Serving Flask app "upload_component" (lazy loading)
* Environment: production
  WARNING: Do not use the development server in a production environment.
  Use a production WSGI server instead.
* Debug mode: on
Running on http://127.0.0.1:8050/
Debugger PIN: 913-207-254
```

# Evaluation

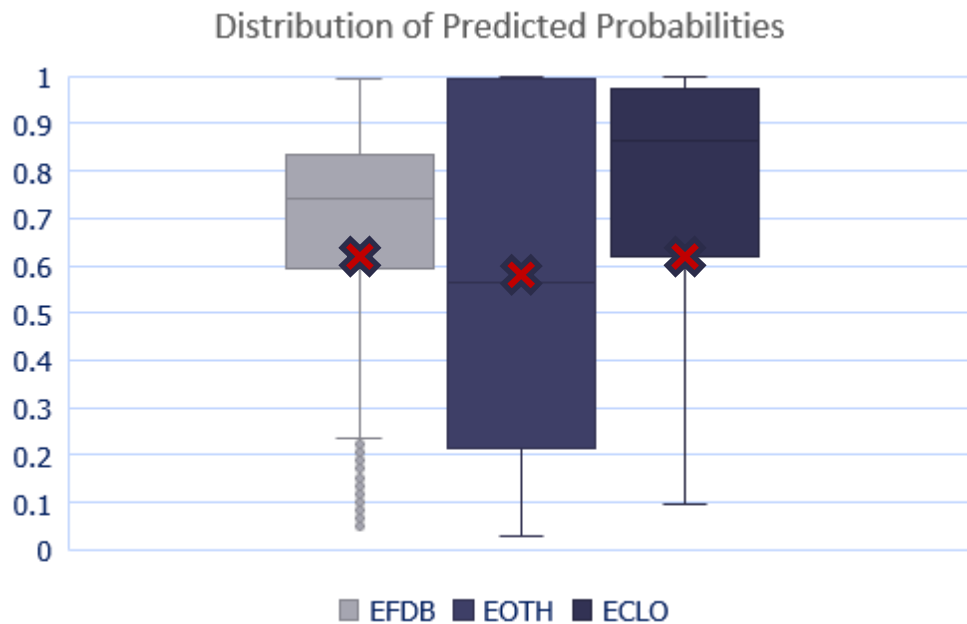
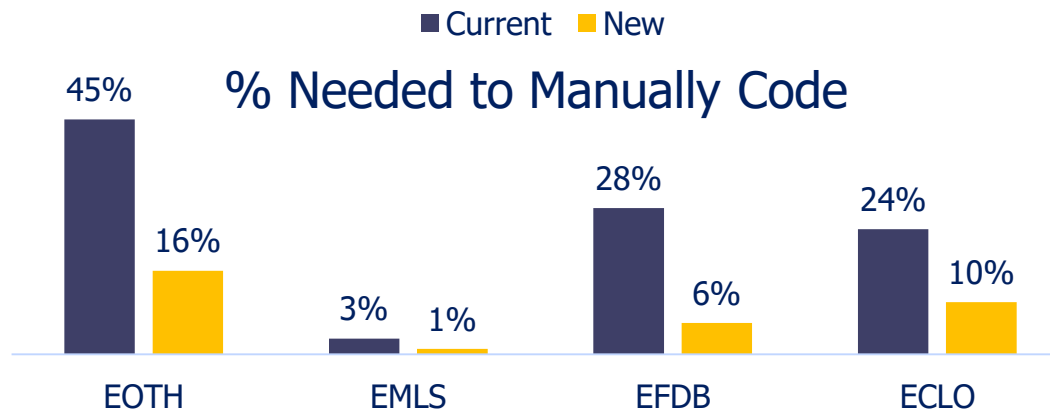
<b>Model</b>	<b>Precision</b>	<b>Recall</b>	<b>F1 Score</b>	<b>Accuracy</b>
<b>Clothing</b>	0.91	0.9	0.9	0.9
<b>Food and Beverages</b>	0.95	0.94	0.94	0.94
<b>Meals</b>	0.98	0.98	0.98	0.98
<b>Other</b>	0.85	0.83	0.83	0.83

# Item Code Probability Distributions



EOTH and EFDB show greater variability in predicted probabilities whereas ECLO shows greater confidence in its predictions.

# Evaluation



# Threshold Evaluation

## Above Threshold

Model	Precision	Recall	F1 Score	Accuracy
Clothing	0.97	0.96	0.97	0.97
Food and Beverages	0.99	0.99	0.99	0.99
Other	0.97	0.97	0.97	0.97

## Below Threshold

Model	Precision	Recall	F1 Score	Accuracy
Clothing	0.802	0.7	0.71	0.7
Food and Beverages	0.87	0.85	0.85	0.85
Other	0.79	0.73	0.72	0.73

# Takeaways

1. Even though **EFDB** has the most number of unique item codes (185), **the codes are the most separable** (least overlap); **ECLO** item codes have **the most overlap**
2. Thresholds can be lowered (less manual coding) to a certain extent without accuracy compromise
3. Misspellings does not impact accuracy that much
  - (ECLO accuracy +0.4% after misspellings fixed)



# Future Work

This autocoder is a **promising proof of concept** for use of machine learning at the BLS.

- **Moving away from Census NPC coding:** Semi-supervised learning methods can predict item codes using past data's target variable without the need for its own
- **Reducing model error:** boosting methods, fix misspellings, dimensionality reduction, more training data (more CPUs), include store name
- **Thresholding for manual classification:** One vs. Rest Classifier ROC curve to determine specific threshold
- **Incorporating BLS expertise:** Diary specific vector embeddings using Genism's Word2Vec

# Thank You!

## Questions?



# Appendix



# Ethics of Machine Learning

Machine Learning uses **past data sets to predict outcomes**, meaning a model is only as good as its data.

## Machine Learning in the Government

Bias and discrimination: [Government Crime Classification Tool Racially Biased](#)

Erosion of Privacy: [Chinese Government Launches Social Credit System](#), [NYC Patrolling Officers Wear Body Cameras](#)

## Machine Learning at the BLS

Models have **preferences**.

```
"pepperoni": "pepper",
```

Automation contributes  
**to workforce  
displacement.**

Automation automates  
**human biases.**

ItemType	ItemCode	ItemDescription
EOTH	821132	ACRYLIC NAILS
EOTH	870048	NAILS
EOTH	314120	COMMON NAILS

*Under what circumstances is autocoding worthwhile?*