CLASSIFYING LABORATORY TEST RESULTS USING MACHINE LEARNING

Joy (Sizhe) Chen, Kenny Chiu, William Lu, Nilgoon Zarei AUGUST 31, 2018





Joy (Sizhe) Chen





Kenny Chiu







Nelly (Nilgoon) Zarei





AGENDA

- Background
- Project Scope
- Dataset
- Machine Learning Approach and Results
- Symbolic Approach and Results
- Pipeline Architecture
- Future Work

BACKGROUND



BACKGROUND

Lab Result

Specimen rejected | Test not performed. | No evidence of HCV infection.

No Bordetella pertussis DNA detected by PCR.

Result inconclusive. | Culture results to follow. | Varicella Zoster Virus | 'Isolated.'

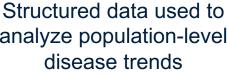
rotypable (non

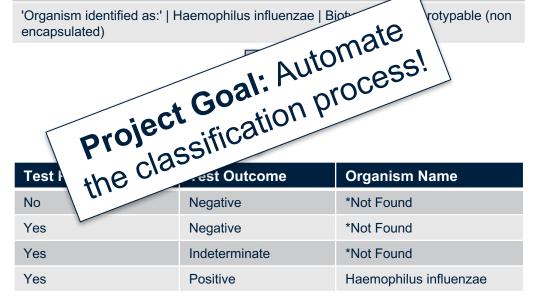
'Organism identified as:' | Haemophilus influenzae | Biotur encapsulated)

Semi-structured free form text data from lab reports containing raw test results

Manual classification process (expensive, slow)

Structured data used to analyze population-level disease trends

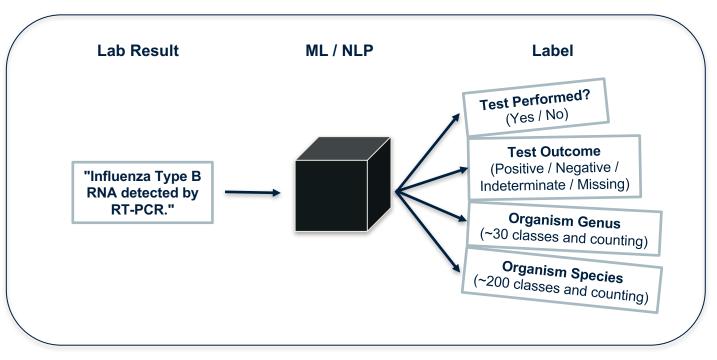






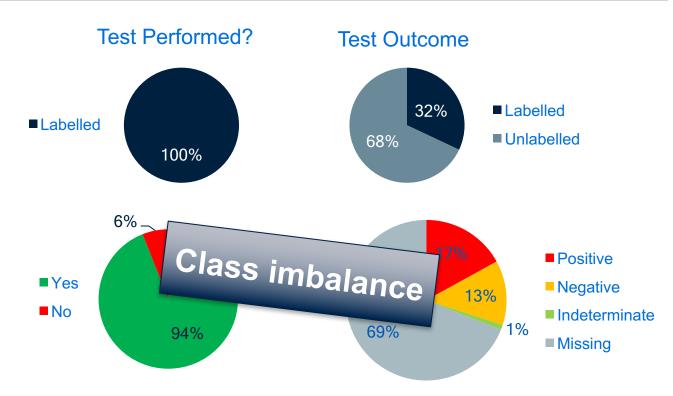
PROJECT SCOPE

Identify, implement, and test appropriate machine learning and natural language processing techniques for interpreting and labeling unstructured lab results

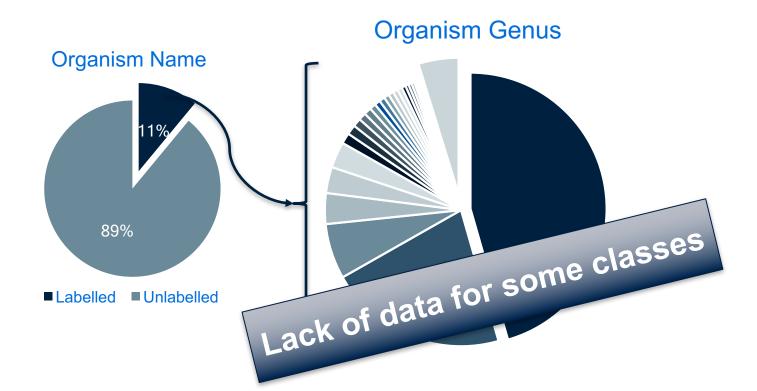




~1 million rows; ~360K usable rows after filtering out proficiency tests and purely numeric results



~1 million rows; ~360K usable rows after filtering out proficiency tests and purely numeric results



positive Mass range entamoeba organism^{hbv}pcr complex species public testing rubella genotype prev assay plood found suggests patients iu considered gene igg spect anti mycobacterium^r • confirmed received report fied due fol reference sample type growth detection may nonpat trophozoites required hbsag discordant obacteria levels per formance erpretatio analysi S

UBC

• Lab results may be incomplete sentences and may contain typographical errors

BCCDC seretype: non froup 5 | Final | 12/Jun/2009 | Sputum | Streptococcus pneumoniae | STUDY

Isolate not | Salmonella species

• Lab results may contain contradictory information

TEST NOT PERFORMED | Galactomannan testing is valid only for Haematology and lung transplant patients with no recent antifungal exposure | Test performed at Provincial Laboratory of Public Health, Edmonton

Organism identified as: | Neisseria meningitidis nongroupable | Upon further investigation | Organism identified as: | **Moraxella osloensis** | by 16S rRNA gene sequence analysis.







• One organism may be positive, while another may be negative

NEGATIVE for Shiga toxin stx1 and stx2 genes by PCR. | Isolate serotyped as: | Escherichia coli | not | O157:H7

• Lots of negative organisms may be mentioned in the result full description

Rhinovirus or **Enterovirus** detected by multiplex NAT. || **Adenovirus** detected by multiplex NAT. | | Multiplex NAT is capable of detecting Influenza A and B, Respiratory Syncytial Virus, Parainfluenza 1, 2, 3, and 4, Rhinovirus, Enterovirus, Adenovirus, Coronaviruses HKU1, NL63, OC43, and 229E, hMetapneumovirus, Bocavirus, C. pneumoniae, L. pneumophila, and M. pneumoniae. || MULTIPLE INFECTION DETECTED





MACHINE LEARNING APPROACH

- · Automatically learn patterns from existing categorized data to categorize new data
- Data is represented in terms of features
- Machine learning model has a number of parameters
 - During training, old data is used to optimize the parameter values
 - During classification on new data, a computation is performed on the new data's features and the optimized parameter values in order to determine the classifications
- Parameters are **fitted to the training data**, thus allowing the model to learn.



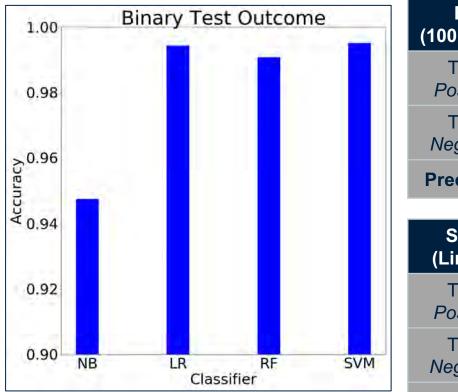
- Started with trivial case: binary Test Outcome (Positive / Negative)
- **Bag-of-words**: represent document by vector of integers that denote number of times each unigram (single word) appears
 - simple and convenient but loses word ordering information

	Unigram	Coun
"Unable to differentiate	differentiate	1
between Streptococcus	identified	0
mitis and Streptococcus	 	
pneumoniae."	streptococcus	2
	unable	1





nt



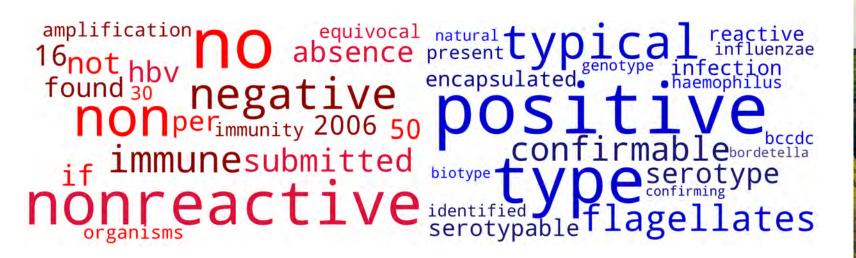
RF (100 trees)	Predicted Positive	Predicted <i>Negative</i>	Recall
True Positive	3860	41	99%
True <i>Negative</i>	16	2987	99%
Precision	99%	99%	
SVM (Linear)	Predicted Positive	Predicted <i>Negative</i>	Recall
True Positive	3885	16	99%
True <i>Negative</i>	9	2994	99%





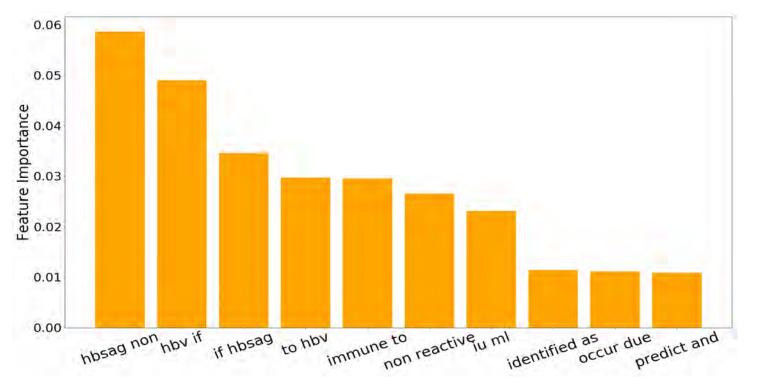


Important unigrams for Negative and Positive based on Logistic Regression weights



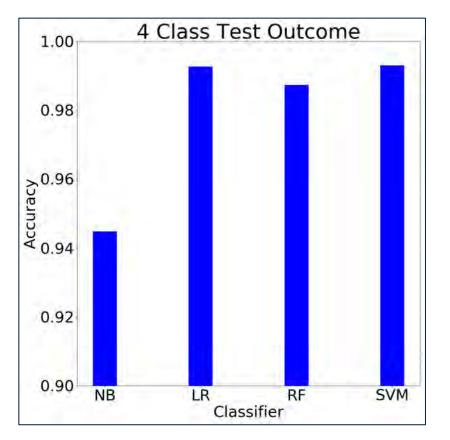


Important bigrams for Test Outcome as ranked by Random Forest



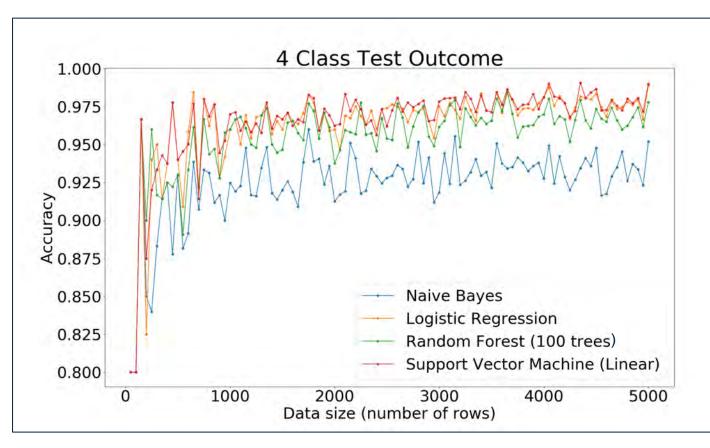
16

RESULTS – 4 CLASS TEST OUTCOME



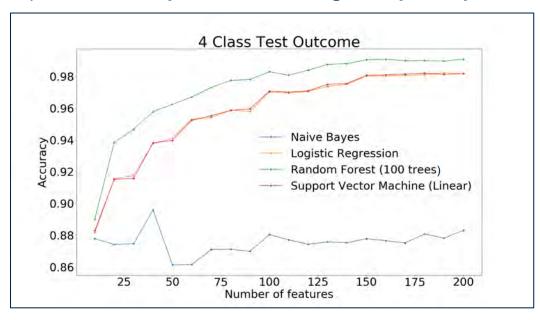


RESULTS – 4 CLASS TEST OUTCOME



RESULTS – FEATURE SELECTION

• Remove unhelpful features to prevent overfitting and speed up training.



• For example, *Test Outcome* classifiers still do well with only 200 unigram features!



Support Vector Machine (Linear): 98% accuracy

SVM (Linear)	Predicted Yes	Predicted No	Recall
True Yes	67696	411	99%
True No	947	3475	79%
Precision	99%	89%	

• **Class imbalance** caused the classifier to over-predict the majority class.

- Strategies to fix this:
 - **Down-sampling** in the training set, randomly throw out rows from the majority class until classes are balanced.
 - Disadvantage: throws out too much training data.
 - **Up-sampling** in the training set, randomly duplicate rows from the minority class until classes are balanced.
 - Disadvantage: takes too long to train.





 Class reweighting – during training, penalize the classifier more for misclassifying minority rows.

Support Vector Machine (Linear): 98% accuracy

SVM (Linear)	Predicted Yes	Predicted No	Recall
True Yes	66355	1800	97%
True No	429	3945	90%
Precision	99%	69%	

• Disadvantage: Reduces false positives at the expense of false negatives.

Add **bigrams** (pairs of consecutive words) and **trigrams** (triples of consecutive words) to the feature space to **boost interpretability** but at the cost of **introducing duplicates**.

Most important <i>Test Performed</i> fe	eatures (ranked by Random Forest)

Unigrams only	Unigrams, bigrams, and trigrams
performed	missing
not	test not
test	test not performed
missing	not performed
routinely	performed
patient	not



SYMBOLIC APPROACH FOR ORGANISM NAME

- **Problems** with the machine learning approach:
 - **Data-hungry** there are not enough labelled rows for some organisms
 - Can't find new organisms there is no complete dictionary of organism names, so an approach is needed
- We must consider an **alternative approach** for classifying organism name.





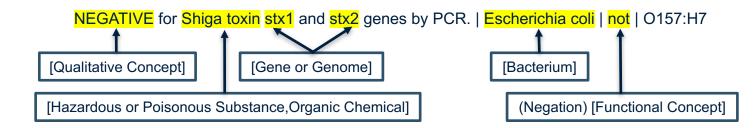
MACHINE LEARNING VS. SYMBOLIC

	Machine Learning	Symbolic
Description	Automatically learn patterns from existing categorized data ("training set") to categorize new data ("test set")	Tag each word by referring to a knowledge base, then apply domain rules to categorize data
Pros	 Adapts to new coding styles More robust to typos and grammatical errors 	 More interpretable Can find labels that do not already exist in the database
Cons	 Data hungry Long training time Requires domain knowledge 	 Long tagging time Requires significant domain knowledge

METAMAP

MetaMap application: annotates text with UMLS Metathesaurus concepts

• e.g. Bacterium, Functional Concept, Finding



Usages:

- 1. Extract all recognized Bacterium and Viruses as microorganisms
- 2. Generalize classifiers by including UMLS concepts as classifier inputs

RESULTS – ORGANISM GENUS

- Training stage: **construct dictionary** of all existing organisms in the database.
- We use a two-part algorithm for classifying Organism Genus label.
 - First, look at Test Outcome classification.

If Test Outcome is negative Organism Genus is "*Not Found" by definition.
 Rhinovirus or Enterovirus detected by multiplex NAT. || Adenovirus detected by multiplex NAT. |
 Multiplex NAT is capable of detecting Influenza A and B, Respiratory Syncytial Virus,
 Parainfluenza 1, 2, 3, and 4, Rhinovirus, Enterovirus, Adenovirus, Coronaviruses HKU1, NL63,
 OC43, and 229E, hMetapneumovirus, Bocavirus, C. pneumoniae, L. pneumophila, and M.
 pneumoniae. || MULTIPLE INFECTION DETECTED

- This approach achieves ~85% accuracy.
 - Fails mostly on rows with lots of negative organisms.



RESULTS – ORGANISM SPECIES

- Training stage: **construct dictionary** mapping genus to possible species.
 - Uses existing genus and species labels in the database.
- We use a **two-part algorithm** again:
 - First, look at Organism Genus classification.
 - If Organism Genus is "*Not Found", Organism Species is "*Not Found".
 - Then, look at the list of organisms recognized by MetaMap:
 - Filter the list, keeping all species corresponding to the *Organism Genus* classification.
 - Arbitrarily pick an organism.
- This approach achieves ~50% accuracy.

RESULTS – TEST OUTCOME GENERALIZABILITY

• Original test outcome classifier did not generalize to unlabelled dataset:

Result Full Description	Test Outcome Prediction
Growth of mycobacteria to be identified. 16A306 Mycobacterium gordonae	*Missing
Mycobacterium tuberculosis complex Identification of species to follow. 11S458 Mycobacterium tuberculosis	*Missing

- Classifier **overfitted** to organism names in training set.
 - Classifier did not recognize "Mycobacterium" as an organism name because it did not appear in the training set.



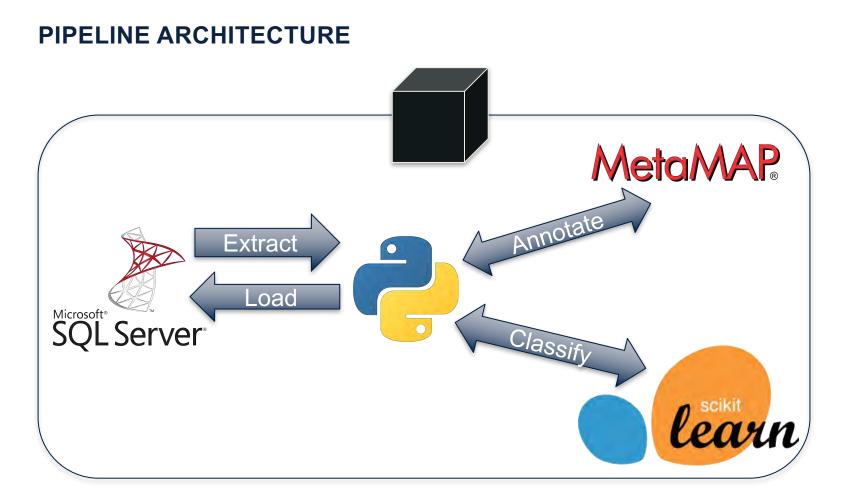
RESULTS – TEST OUTCOME GENERALIZABILITY

- Solution: **replace organism names** with special "_ORGANISM_" token.
 - Use MetaMap to identify organism names in the input text.

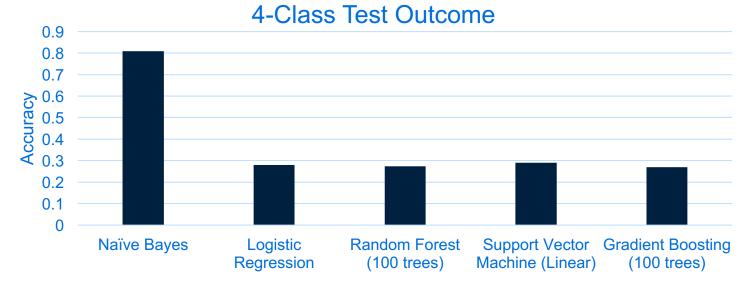
Result Full Description	Test Outcome Prediction
Growth of _ORGANISM_ to be identified. 16A306 _ORGANISM_	Positive
ORGANISM complex Identification of species to follow. 11S458 _ORGANISM_	Positive

Feature engineering





 Use all labelled antibody tests as training set, use all labelled NAT/PCR tests as testing set.



- Naïve Bayes likely worked well by chance.
- This hints that we should train **separate classifiers for different test types**.

Here



Classify data at the **observation level** to detect which organisms were positive. .

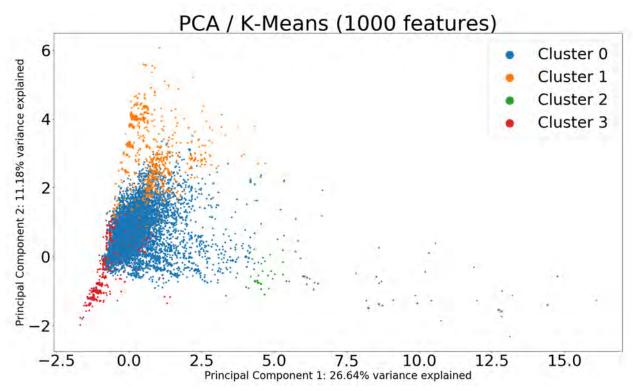
NEGATIVE for Shiga toxin stx1 and stx2 genes by PCR. Isolate serotyped as: Escherichia coli not O157:H7				
Result Description	Test Outcome	Organism Name		
NEGATIVE for Shiga toxin stx1 and stx2 genes by PCR.	Negative	Shiga toxin stx1 / stx2		
Isolate serotyped as: Escherichia coli not O157:H7	Positive	Escherichia coli non-o157 h7		

- **Challenge:** no labelled data given at the observation level. •
 - Workaround: Train at the test level, classify at the observation level. ٠
 - Either relabel data **manually** or use **clustering**. ٠



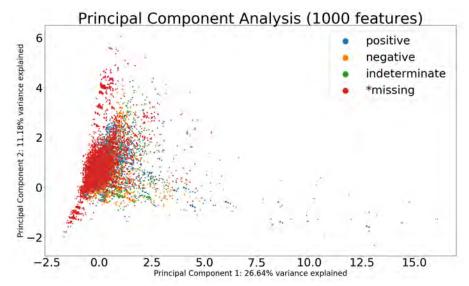


• Use clustering to find patterns in unlabelled data.





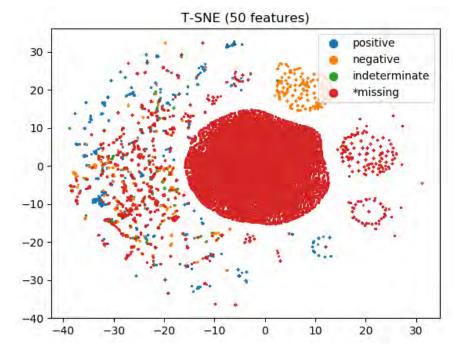
 Principal Component Analysis – project the data into a 2D space that explains the most variance between the data points



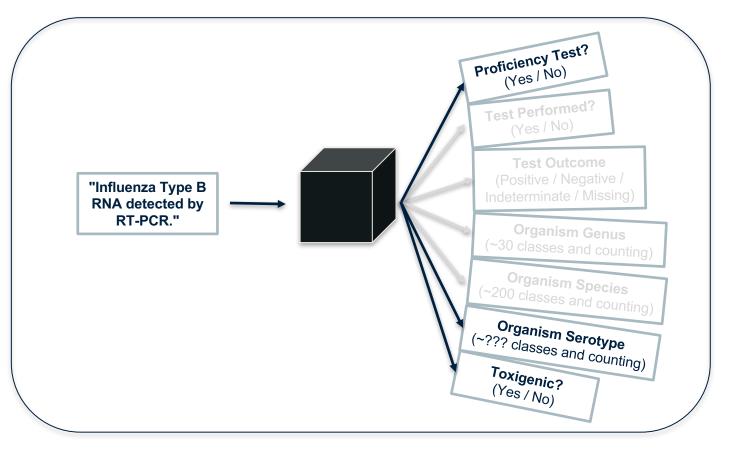
- This hints that we should try other clustering methods (hierarchical, etc.)
- However, **sum of variance explained is below 50%**, so interpretation is dangerous.



• **t-distributed stochastic neighbour embedding** – identify a 2D "surface" that the data points reside on, and create a visualization by flattening that surface









• Ensemble methods (stacking): Flag a row for human processing if enough classifiers disagree.

	Individual Class	sifier Predictio	ı	Einal Dradi
NB	LR	RF	SVM	Final Predic
Yes	Yes	Yes	Yes	Yes
Yes	No	Yes	No	Flag
No	No	No	Yes	No
No	Yes	Yes	No	Flag

• Look into classifier confidence measures to flag rows as well.









- Training separate classifiers for separate test types, replacing organism names, and classifying at the observation level are **not well tested**.
- Classifier still exhibits generalizability issues.
- Future work should aim to improve generalizability.
 - Feature engineering (removing dates, etc.)
 - Meet with a domain expert to obtain a list of domain-specific stop words.



QUESTIONS?