



# AI-Assisted Coding for Transcript Data

**FedCASIC**  
**April 2021**

Colleen Spagnardi, RTI International  
Alex Waldrop, RTI International

**PILOT**

|

**METHODS**

|

**QUESTIONS**

# What is the study?

---

## **National, Longitudinal Study**

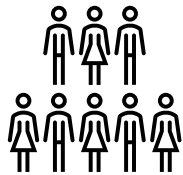
Surveys students during and following postsecondary careers and collects transcripts

### **Transcripts provide:**

- Enrollment and transfer credit
- Degrees and field of study
- Coursework attempted and completed

# What's the challenge?

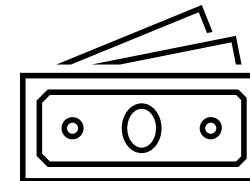
>40K transcripts,  
500K courses



**Staff**

|     |     |     |
|-----|-----|-----|
| JAN | FEB | MAR |
| APR | MAY | JUN |
| JUL | AUG | SEP |
| OCT | NOV | DEC |

**Duration**



**Cost**

# What's the goal?

## CURRENT STATE: Manual

Manual coding

Double coding of 10%

## PILOT: AI Assisted

AI-assisted recommendations

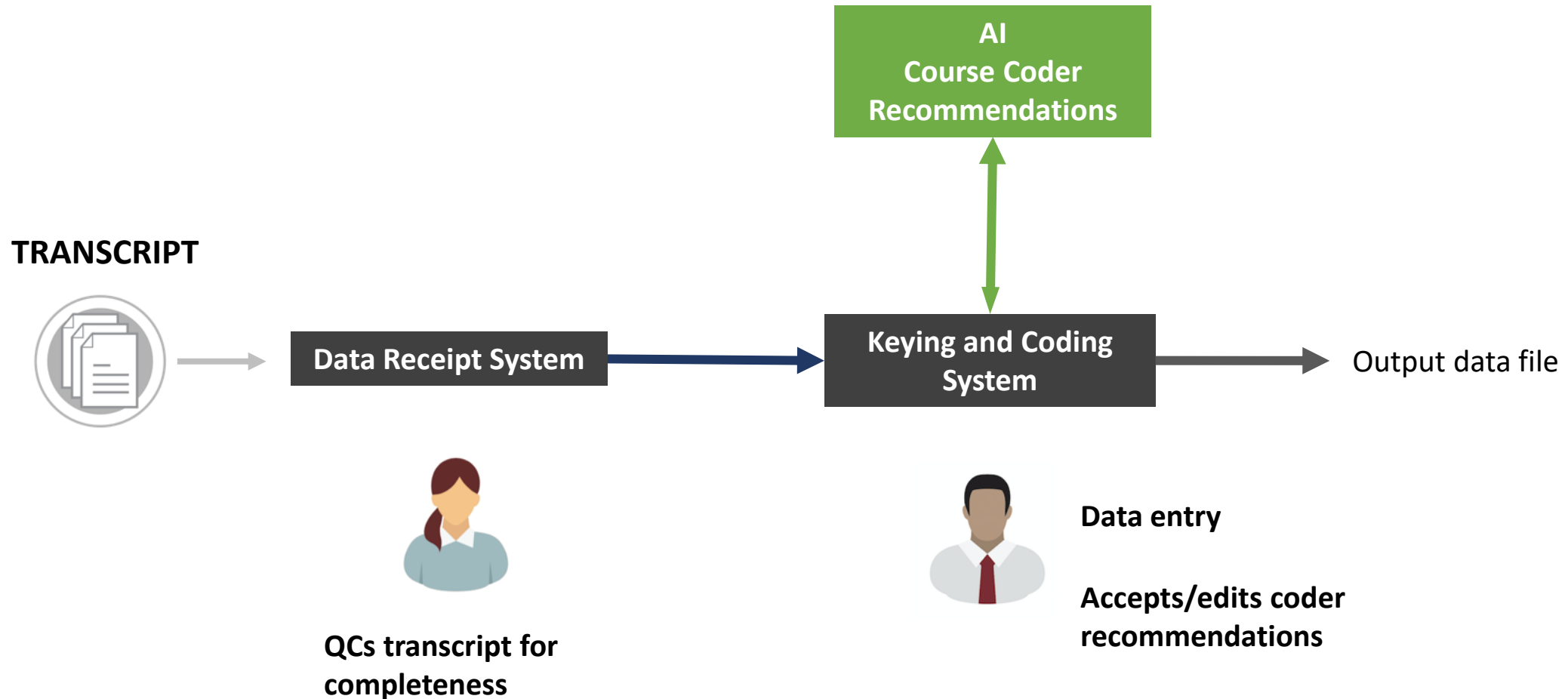
Double coding of 10%

## FUTURE: Human Assisted

Auto coding of majority

Double coding only difficult cases

# How does it work?



# **What is course coding?**

# COURSE CODES

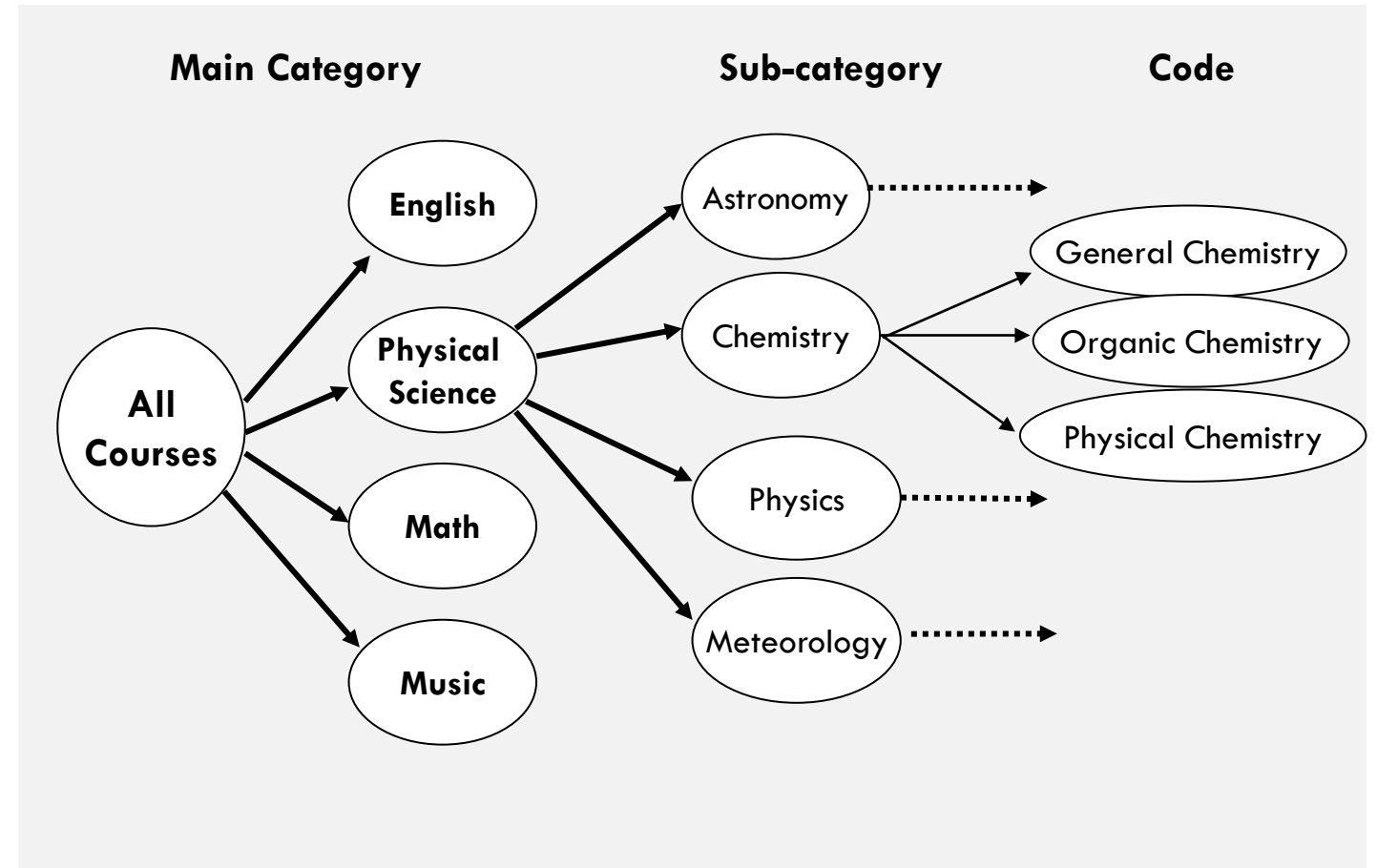
## College Course Map (CCM)

23 . 13 01

2-digit  
General category

4-digit  
Sub-category

6-digit  
Specific subject



**Coding:** Assigning the best code based on the course title and description



## MANUAL

---

Code suggestions are based on key word search and staff look up descriptions in an online or PDF catalog

VS.

## AI ASSISTED

---

Suggests probable matches to a course name using historical data

**Is it possible to improve  
course coding efficiency  
and accuracy?**

# EFFICIENCY

Coding courses  
was faster with  
enhancements

## TIME SAVINGS PER COURSE

**7 seconds**

Course Coder

for 200K courses, ~400 total hours saved

# ACCURACY

(Agreement between human coders)

Agreement  
rates increased

Agreement rates on 10% of courses (21K of 200K coded)

|                            | Before<br>recommendations | After<br>recommendations |
|----------------------------|---------------------------|--------------------------|
| General category (2-digit) | .84                       | .85                      |
| Subcategory (4-digit)      | .74                       | .76                      |
| Specific (6-digit)         | .62                       | .65                      |

KAPPA SCORE measures inter-rater reliability

- 0.81–1.00 = “almost perfect agreement”
- 0.61–0.81 = “substantial agreement”

# ACCURACY

(Agreement with recommendations)

Coders chose one of the recommended codes 90% of the time

## Agreement with Recommendation

| Measure         | Courses |
|-----------------|---------|
| Top 1 Agreement | 69%     |
| Top 5 Agreement | 90%     |

## Selection Frequency

| Recommended Code (ranked) | Courses |
|---------------------------|---------|
| 1                         | 69%     |
| 2                         | 12%     |
| 3                         | 5%      |
| 4                         | 2%      |
| 5                         | 1%      |

Agreement rates on >200K courses

**We can auto code 70% of courses with the same level of accuracy as human coding.**

**Human accuracy threshold = 80%**

# Example 1: High Predicted Probability

Input

|               |                 |
|---------------|-----------------|
| Course Number | SPC1026         |
| Course Name   | Public Speaking |




Output

| Rank | CCM Code | Probability | Title   |
|------|----------|-------------|---|
| 1    | 09.0196  | 0.99        | Public Speaking, Debate and/or Forensics.   |
| 2    | 09.0101  | 0.01        | Speech Communication and Rhetoric.  |
| 3    | 23.9987  | 0.00        | Remedial Speech, Basic Speech, Basic Oral Communication, Basic Oral Skills and/or Listening Skills. |
| 4    | 52.0808  | 0.00        | Public Finance.   |
| 5    | 09.0900  | 0.00        | Public Relations, Advertising, and Applied Communication.   |

# Example 2: Lower Predicted Probability

## Input

|               |                  |
|---------------|------------------|
| Course Number | MATH 151         |
| Course Name   | Precalculus Math |



## Output

| Rank | CCM Code | Probability | Title  |
|------|----------|-------------|--|
| 1    | 27.0198  | 0.42        | Pre-Collegiate Math General, Basic Concepts of Math, Elementary Math, Introductory Math, Developmental Math and/or Preparatory Math. |
| 2    | 27.0101  | 0.40        | Mathematics, General.  |
| 3    | 27.9996  | 0.16        | Analytic Geometry, Elementary Functions and/or pre-calculus.   |
| 4    | 27.9989  | 0.00        | Collegiate Business Math, Math for Business, Math for Economics, Math Accounting and/or Business Algebra.                            |
| 5    | 27.9999  | 0.00        | Mathematics and Statistics, Other.   |



# Double coding

## TO DATE

Random selection of 10% of courses

## NEXT ROUND

Selection within the 30% of difficult courses only

Could double code all 30% to gather data to refine Course Coder over time and increase accuracy of auto-coding the "30%"

## FUTURE

Decrease number of courses needing to be double coded over time

**What are the implications  
of the findings?**

**Auto coding  
saves time  
without  
sacrificing  
accuracy**

For a study with 200K courses,

Auto code: 140K

Manual code: 60K

### **Savings**

2,300+ hours in coding

Reduction of QC for auto coded courses

More efficient and faster leads to fewer temporary staff

PILOT

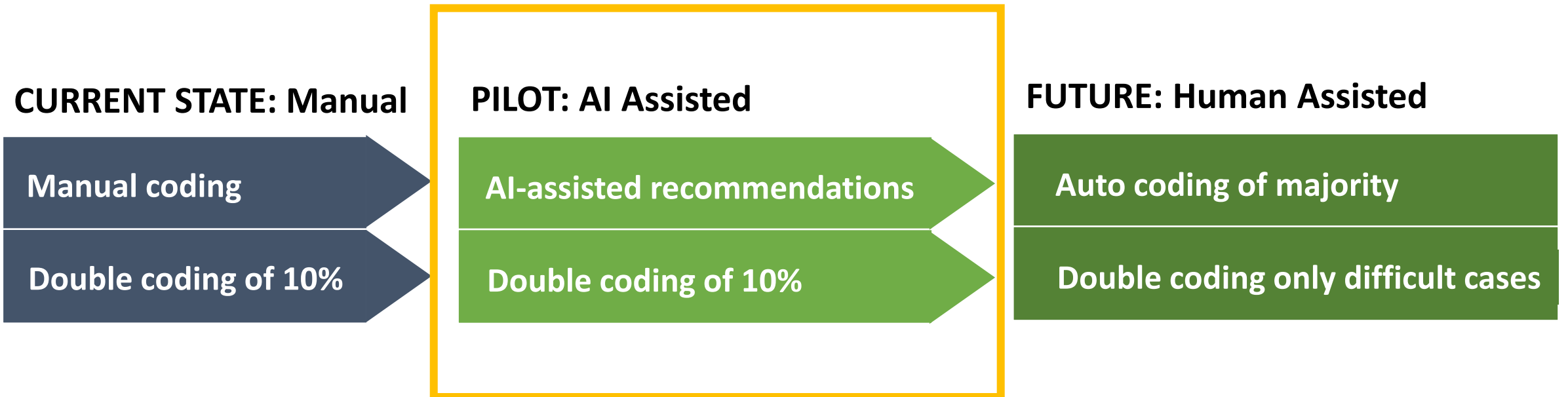
|

METHODS

|

QUESTIONS

# Developing AI model for course coding



# METHODS

---

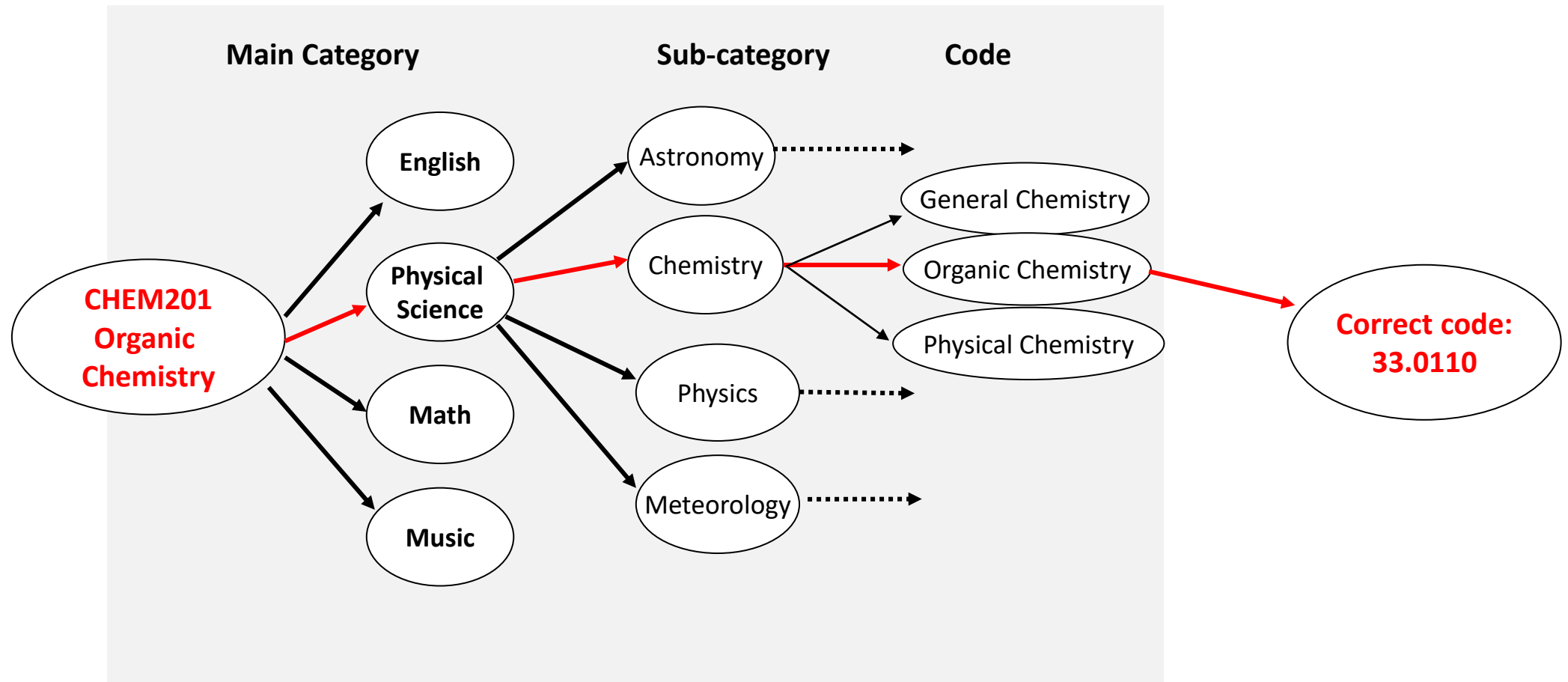
1. What is the technical problem?
2. Machine learning (ML) background
3. How we applied ML to automate course coding

# METHODS

---

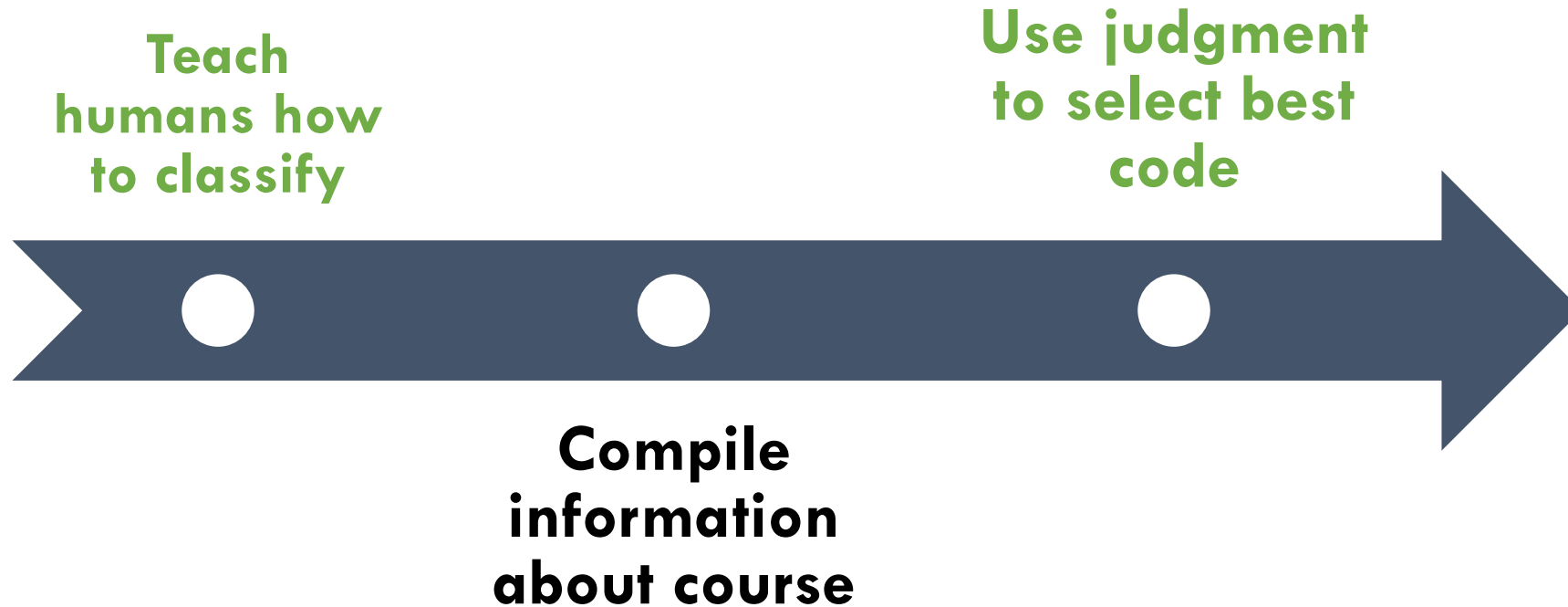
1. What is the technical problem?
2. Machine learning (ML) background
3. How we applied ML to automate course coding

# Course coding makes intuitive sense to humans

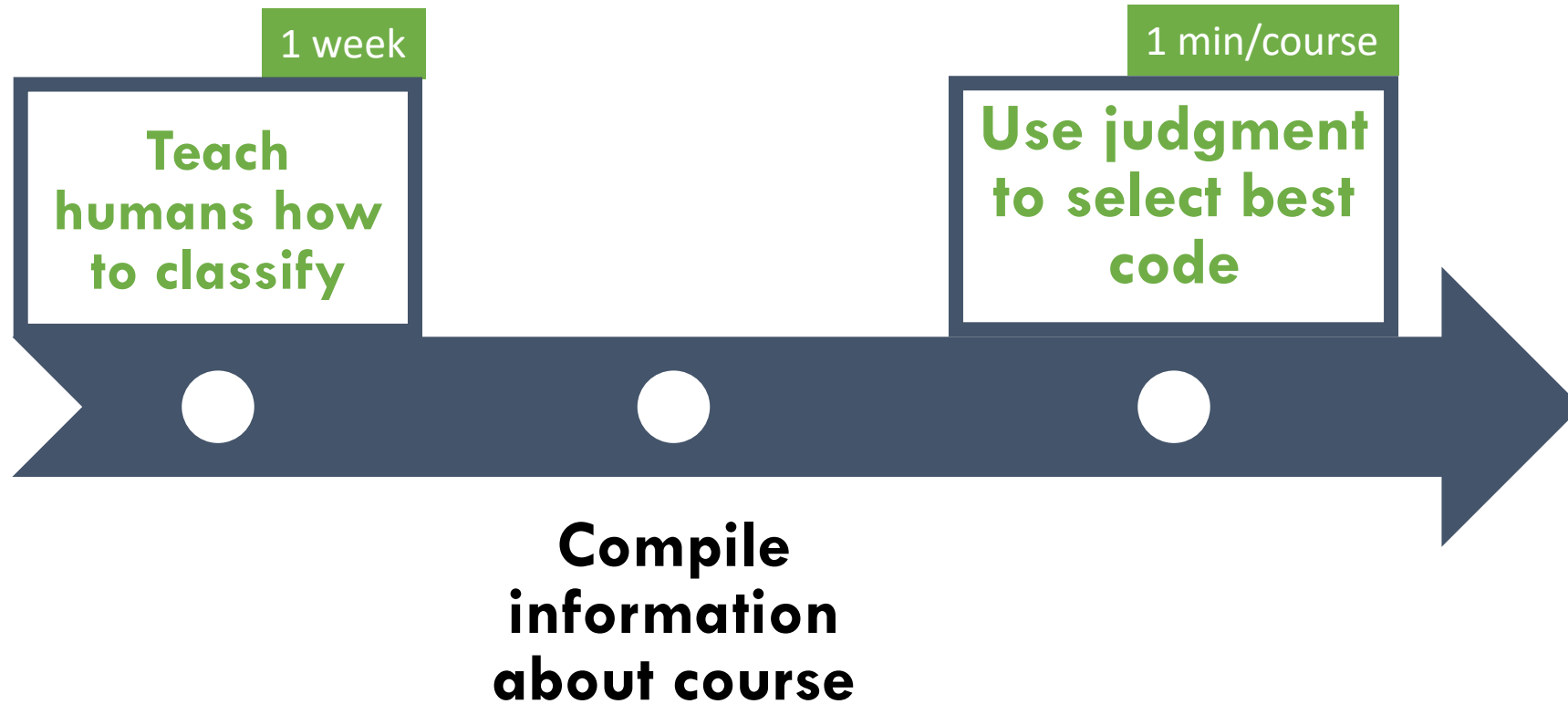




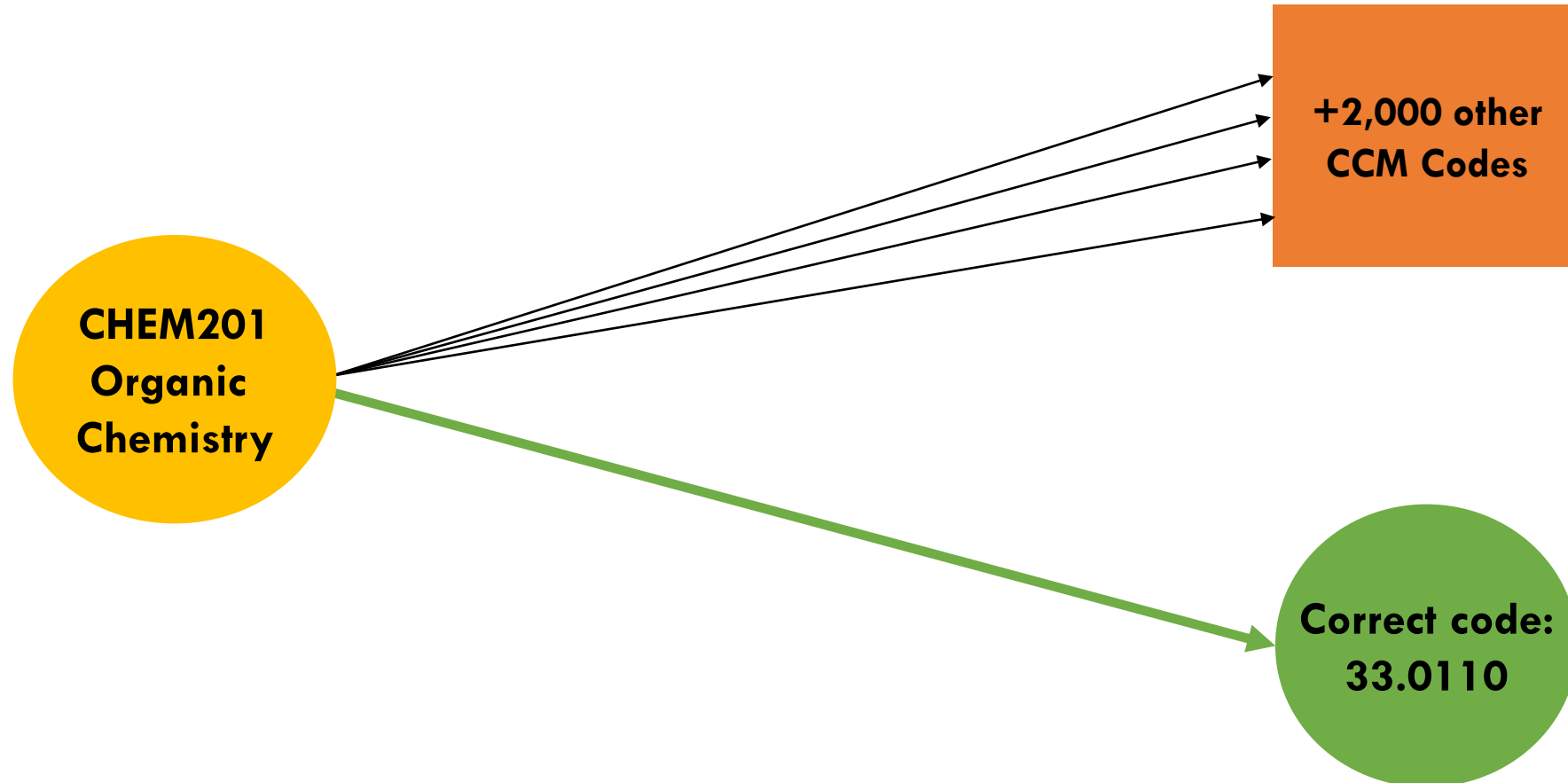
# Coding courses is relatively easy for humans...



# But it's also slow...



# Course coding is a highly-dimensional text classification problem



# How can we automate these steps computationally?

- "Intuitive" problems for humans rely on subjective knowledge about the world
- Impossible to develop "rule-based" system to classify all courses

Course Number SPC1026

Course Name Public Speaking

Course Number BIO151

Course Name Ecology and Evolution

Course Number HIST573

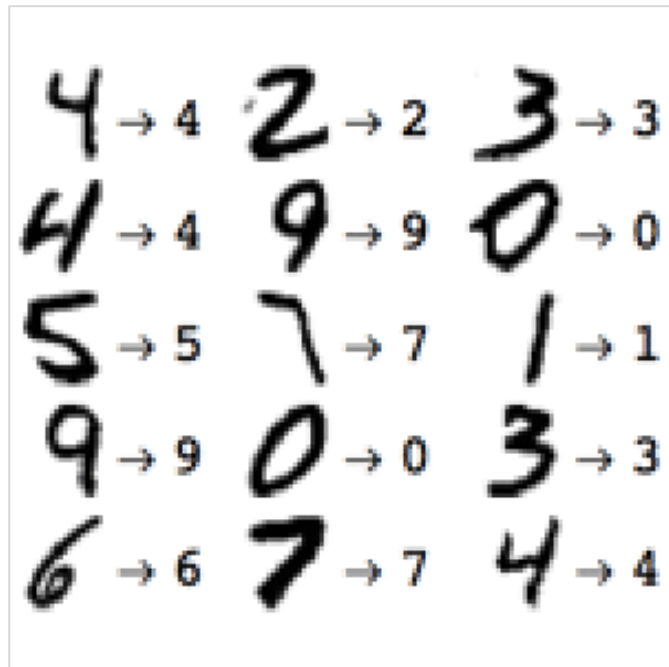
Course Name Gulf War

# METHODS

---

1. What is the technical problem?
2. **Machine learning (ML) background**
3. How we applied ML to automate course coding

# Machine learning is a powerful tool for solving similarly intuitive problems



## Classifying hand-written digits

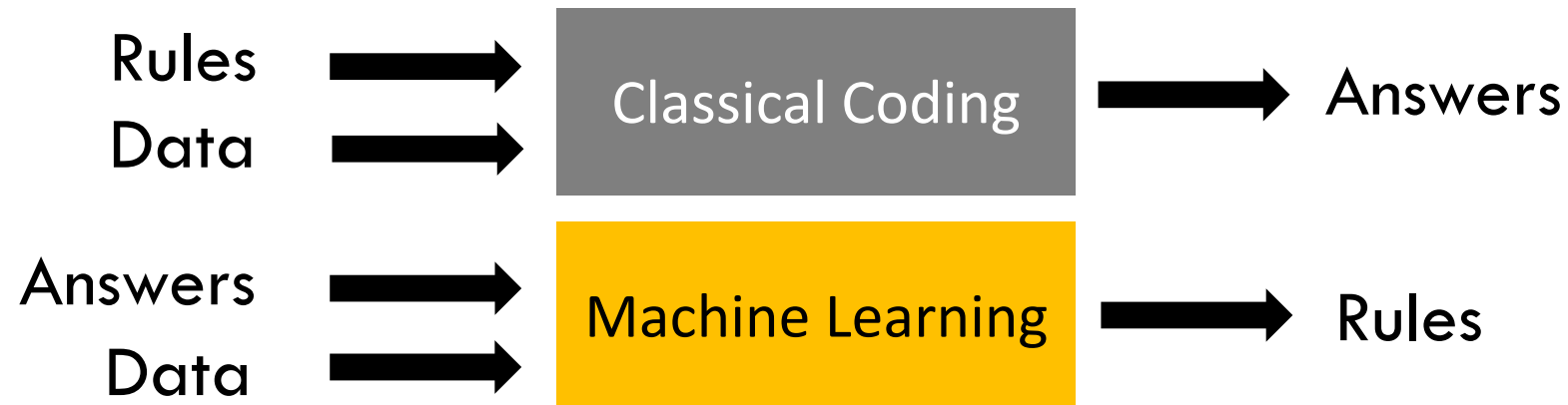
Source: <https://www.wolfram.com/language/11/neural-networks/digit-classification.html?product=language>



## Classifying human facial expressions

Source: Chen et al. (2014) Facial Expression Recognition Based on Facial Components Detection and HOG Features. Scientific Cooperations International Workshops on Electrical and Computer Engineering Subfields 22-23 August 2014, Koc University, ISTANBUL/TURKEY

# ML uses past experiences to "learn" the rules we may not be able to easily articulate



Adapted from: Chollet, Francois. Deep learning with Python. Shelter Island, NY: Manning Publications Co, 2018.

- Model updates it's internal rules as it sees more examples
- Generalized rules can be applied to unseen data with similar performance

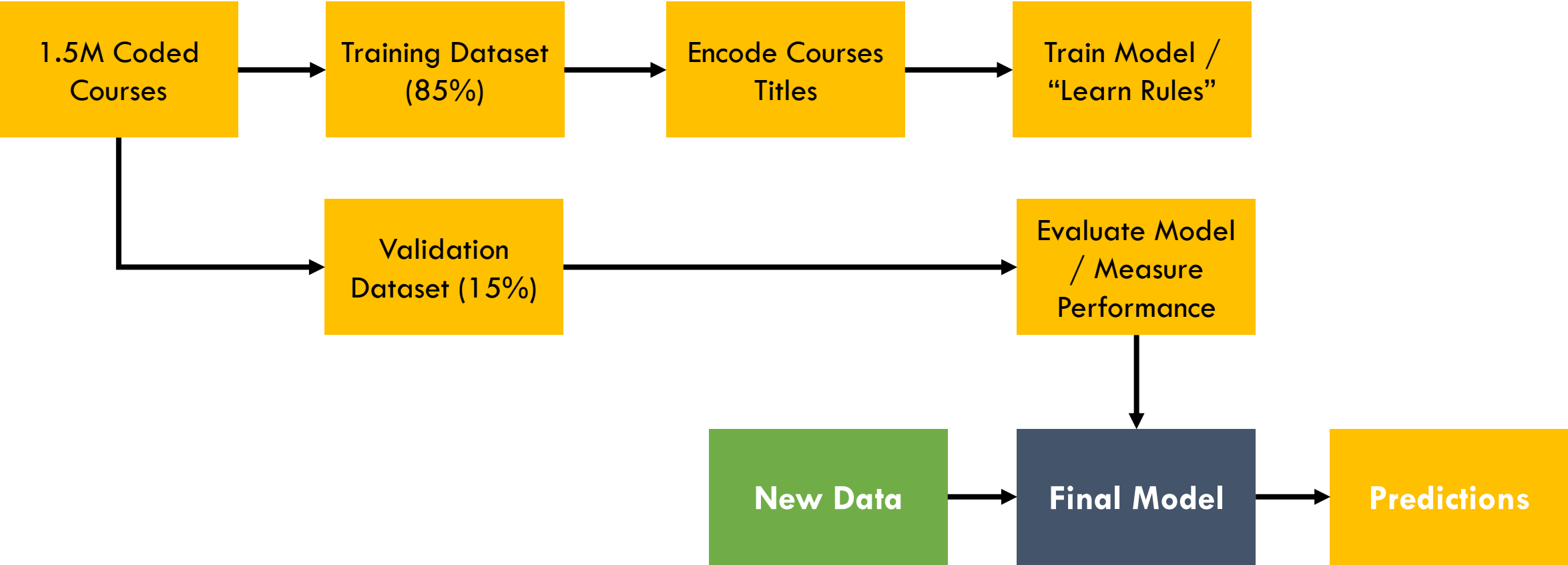
# METHODS

---

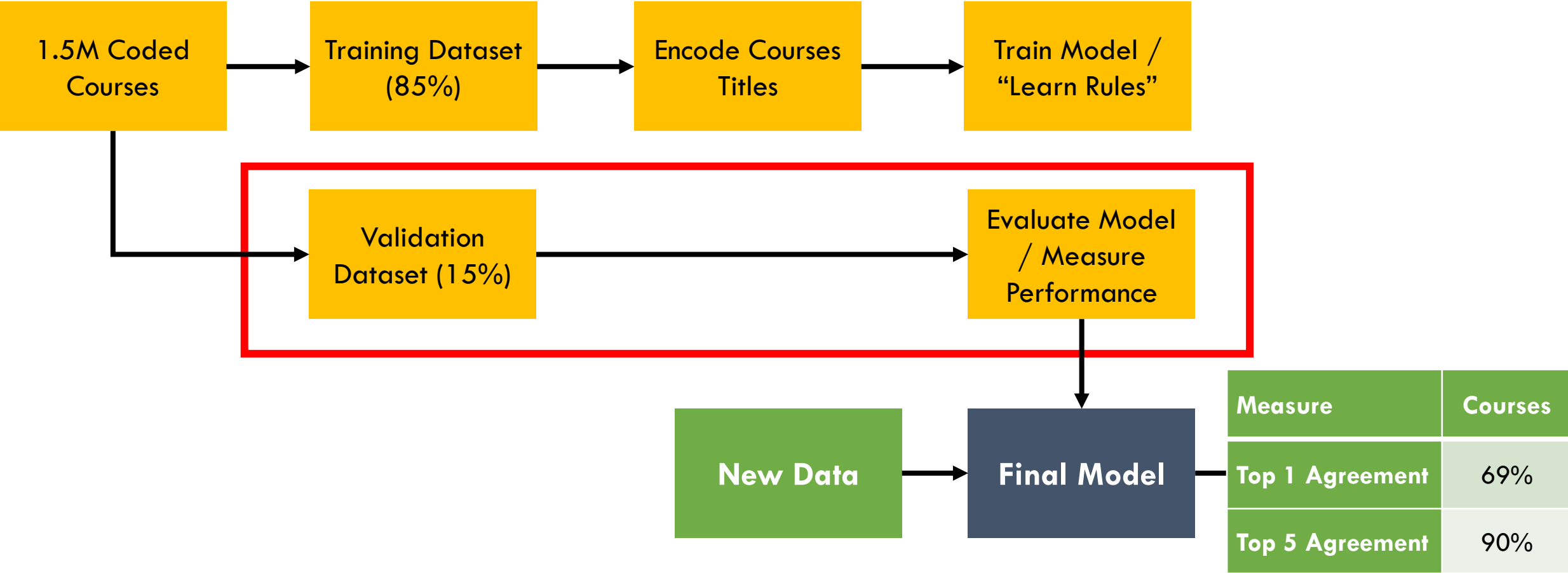
1. What is the technical problem?
2. Machine learning (ML) background
3. **How we applied ML to automate course coding**



# How we built our deep learning college course coder



# Evaluate final model performance on past experiences that weren't included in the training set



# SUMMARY

- AI is not just helpful in theory.  
Demonstrated measurable gains in efficiency without sacrificing quality on RTI projects by using AI solutions.
- AI can expand the scope of the problems we can solve and questions we can answer.

# THANK YOU!

Colleen Spagnardi  
RTI International  
[cspagnardi@rti.org](mailto:cspagnardi@rti.org)  
919-541-6007