Comparing Coding of Interviewer Question-Asking Behaviors Using Recurrent Neural Networks to Human Coders

Jerry Timbrook
University of Nebraska-Lincoln

Adam Eck
Oberlin College

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Behavior Coding

- **Objective, reliable method for coding interaction between interviewers and respondents** (Fowler & Cannell 1996)
- **Description of *actions* during each conversational turn in an interview**

	Behavior Codes		
Conversational turns	Actor	Initial action	Assessment
I: What is your sex?	Interviewer	Question asking	Read exactly as worded
R: Uh, could you repeat the question please?	Respondent	Clarification	Ask for repeat of question
I: What is your sex?	Interviewer	Probing	Repeat question exactly as worded
R: Oh, female.	Respondent	Answer provided	Adequate

Why Do We Need Behavior Coding?

- **Uses:**
  - Pre-test survey questions (Fowler & Cannell 1996)
  - Gain insight into the interviewers' and respondents' cognitive processing (Fowler & Cannell 1996; Schaeffer & Maynard 1996)
  - Evaluate interviewers' performance during the field period (Fowler & Mangione 1990)
  - Evaluate interviewers' effect on measurement (e.g., Dykema et al. 1997; Garbarski et al. 2016; Sarwar et al. 2017; Olson et al. 2018)
- **In short: Behavior Coding helps us understand how respondents and interviewers affect data quality.**

The Present Study

- **The problem:**
  - Behavior coding is typically a manual process
    - Costly and time-consuming
- **The question:**
  - Can we partially automate this coding process using machine learning?
- **The scope:**
  - Focusing on:
    - Interviewer's deviations from exact question readings (question-asking behavior)

Conversational turns	Actor	Initial action	Assessment
I: What is your sex?	Interviewer	Question asking	Read exactly as worded

Why Focus on Question-Asking Behaviors?

- **Standardized Question-Asking** (Fowler & Mangione 1990)
  - Each question is read exactly as worded
  - Why?
    - Ensures all respondents receive the same question wording
      - PIs and data users assume that questions are read exactly as worded in the questionnaire
    - Allows replicability
    - Reduces interviewer variance
      - ↑ interviewer variance = ↓ precision of estimates (wider CI's)
  - Deviations = indicator of problems
    - Lack of interviewer training and monitoring (Fowler & Mangione 1990)
    - Lack of interviewer motivation (Japec 2008)
    - Poor question construction (Oksenberg, Cannell, & Kalton 1991)

Question-Asking Behaviors

- **What are the common classifications for question-asking behaviors?**

We would like to end with a few questions about you and your household. I have to read every question in this survey, even if it seems obvious. What is your sex?

1 MALE
2 FEMALE
3 OTHER, SPECIFY [TEXT BOX]
9 REFUSED

Question-Asking Behaviors

- **Exact Reading**
  - Interviewer reads the question exactly as worded in questionnaire

> We would like to end with a few questions about you and your household. I have to read every question in this survey, even if it seems obvious. What is your sex?

- **Minor Change**
  - Read with one or more words omitted or added
  - Meaning of the question does not change

> *Ok so,* we would like to end with a few questions about you and your household. I *do* have to read every question in *the* survey, even if it seems obvious. What is your sex?

Question-Asking Behaviors

- **Exact Reading**
  - Interviewer reads the question exactly as worded in questionnaire

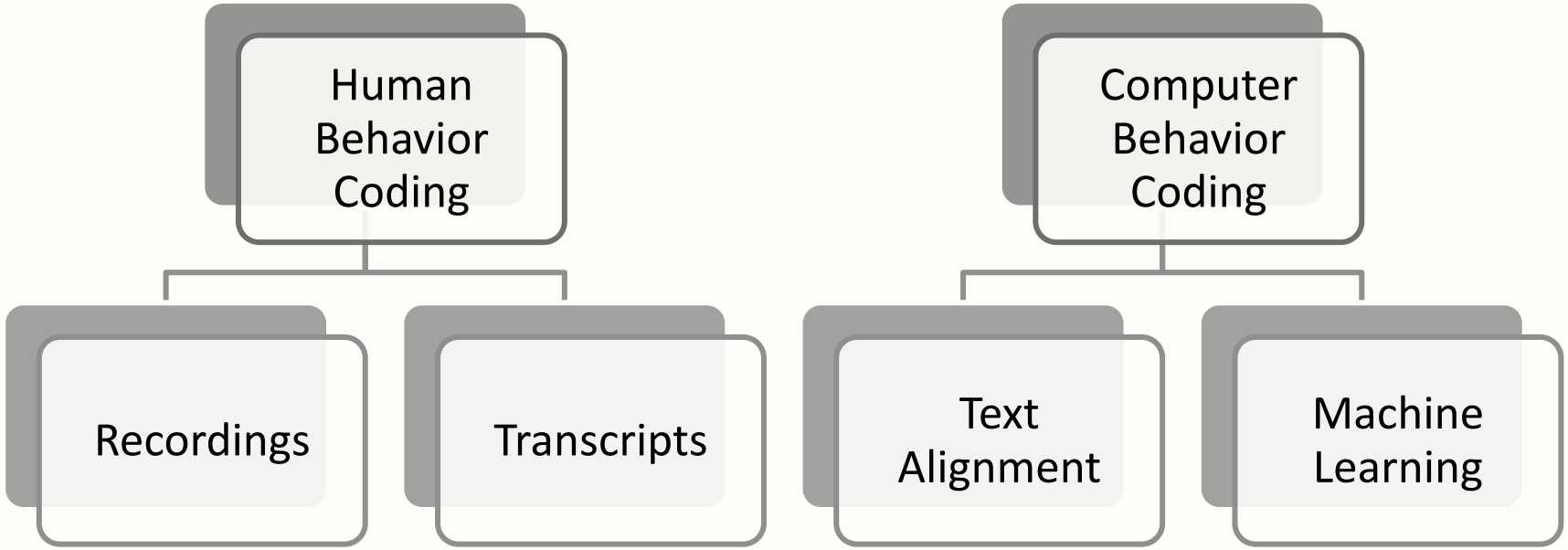
> We would like to end with a few questions about you and your household. I have to read every question in this survey, even if it seems obvious. What is your sex?

- **Major Change**
  - Omission or addition of words that alter question meaning

> We would like to end with a few questions about you and your household.
> I have to read every question in *the* survey, even if it seems obvious.
> What is your sex*, male or female*?

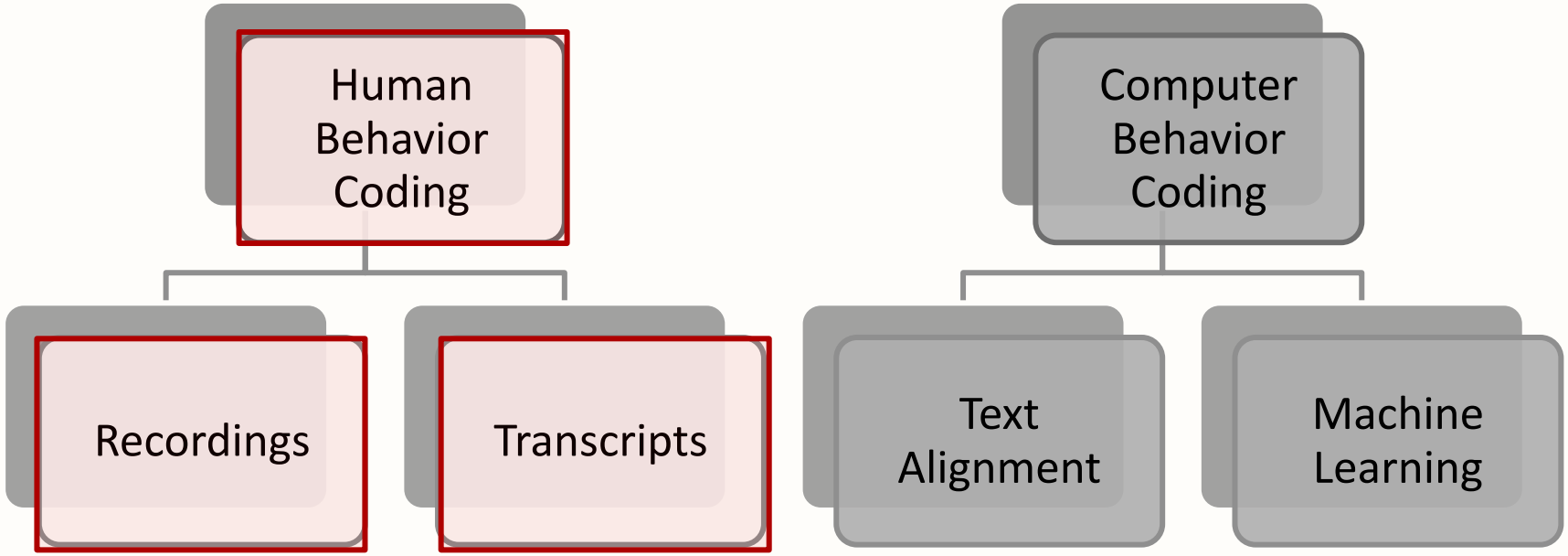
Question-Asking Behaviors

- **What methods are used to code question-asking behaviors?**



Question-Asking Behaviors

- **What methods are used to code question-asking behaviors?**



Human Behavior Coding

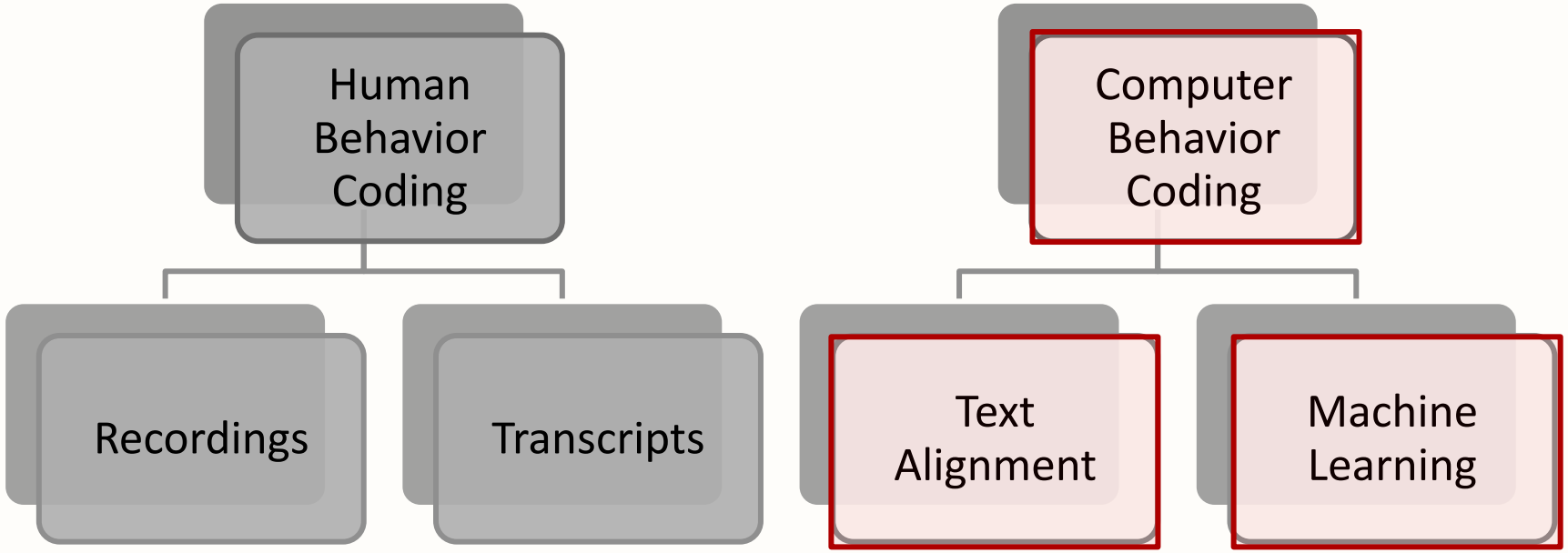
- **Interview Recordings & Transcripts**
  - Transcripts of each case are created using audio recordings of each survey interview
  - A human reads the transcript of each question administration
    - Can also listen if audio recordings are available
  - Assigns a behavior code based on what they read

Human Behavior Coding

- **Interview Recordings & Transcripts**
  - Pros
    - Easy visual review of the question (transcript)
    - Hear the question as it was administered (recording)
      - Timestamps of conversational turns in audio allows for calculating speaking time
  - Cons
    - Potential for human error in coding
    - Error in transcription can lead to error in coding
    - Time consuming and expensive
      - 902 cases
        - (1,680 hours)($11/hour) = $18,480 for transcription
        - (1,163 hours)($11/hour) = $12,793 for coding
        - ($18,480 transcription) + ($12,793 coding) = $31,273

Question-Asking Behaviors

- **How do we classify question-asking behaviors?**



Computer Behavior Coding

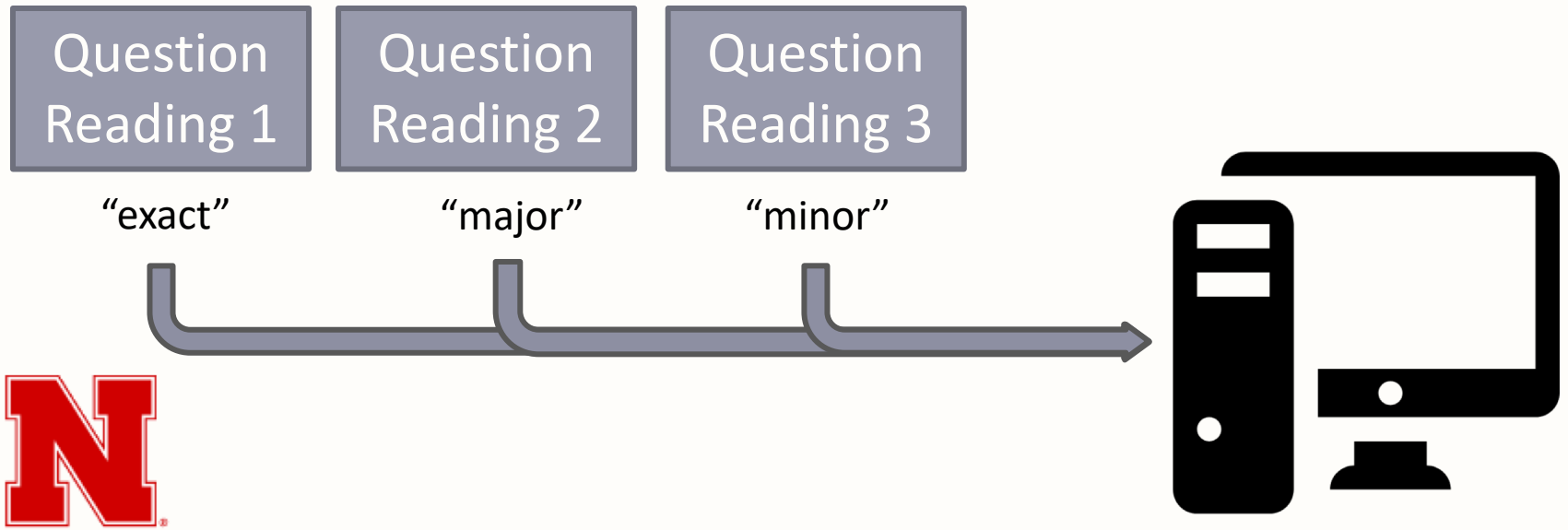
- **Text Alignment**
  - Transcripts required
  - Write computer code that compares the text of each question-reading with the questionnaire
  - Exact Match Method
    - Coded as *exact reading* if the two texts are an identical match
    - Coded as *not exact* if the two texts deviate at all
  - Percent Similarity Method (Distance)
    - Use algorithms to determine percentage of characters in the question-reading text that match the questionnaire text
      - e.g., Levenshtein Algorithm, Trigram Comparison, Jaro-Winkler, Ratcliff/Obershelp
    - Coded as *exact reading* if the percentage is >= some cutoff (e.g., 90%)
    - Coded as *not exact* if the percentage is < the cutoff

Computer Behavior Coding

- **Text Alignment**
  - Pros
    - No human behavior coding required
    - No extra “per case” cost once code is written for a question
    - % Similarity:
      - Allows for some breaks in fluent speech (e.g., uh, um)
      - Allows for some transcription errors (e.g., spelling)
  - Cons
    - Cannot differentiate between major and minor changes
    - % Similarity:
      - Cutoff percentage is arbitrary, may change by question

Methods for Identifying Deviations from Exact Reading

- **Machine Learning**
  - Computer learns to accomplish a task on its own using examples
  - Common Process:
    - Training: Humans provide examples (e.g., transcripts) and their classifications (e.g., behavior codes) as input, computer discovers patterns



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    - Validation: Given additional examples (e.g., transcripts), check overfitting

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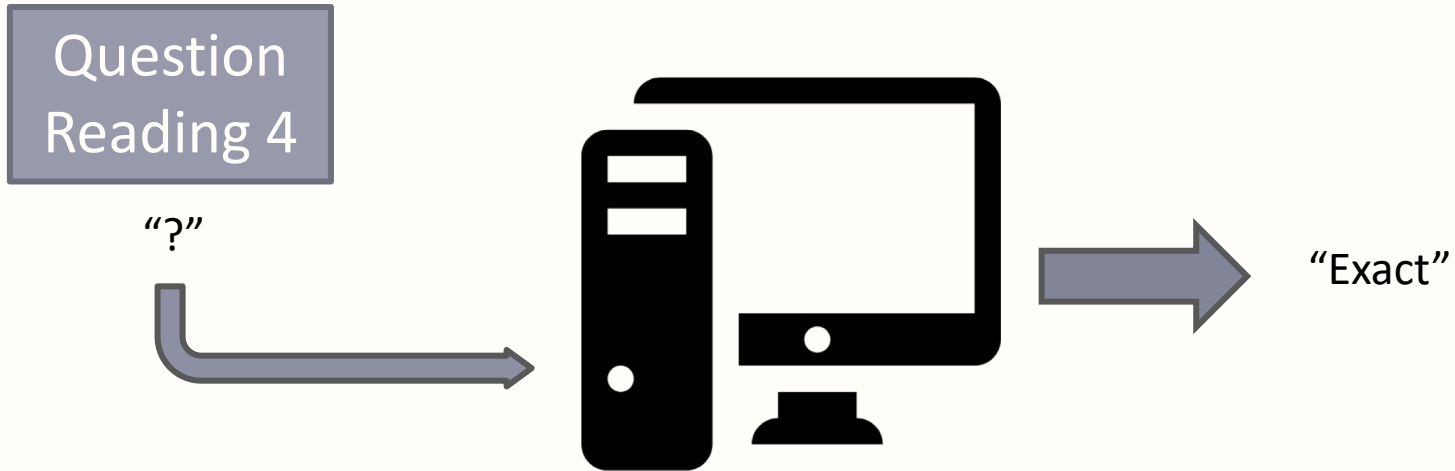
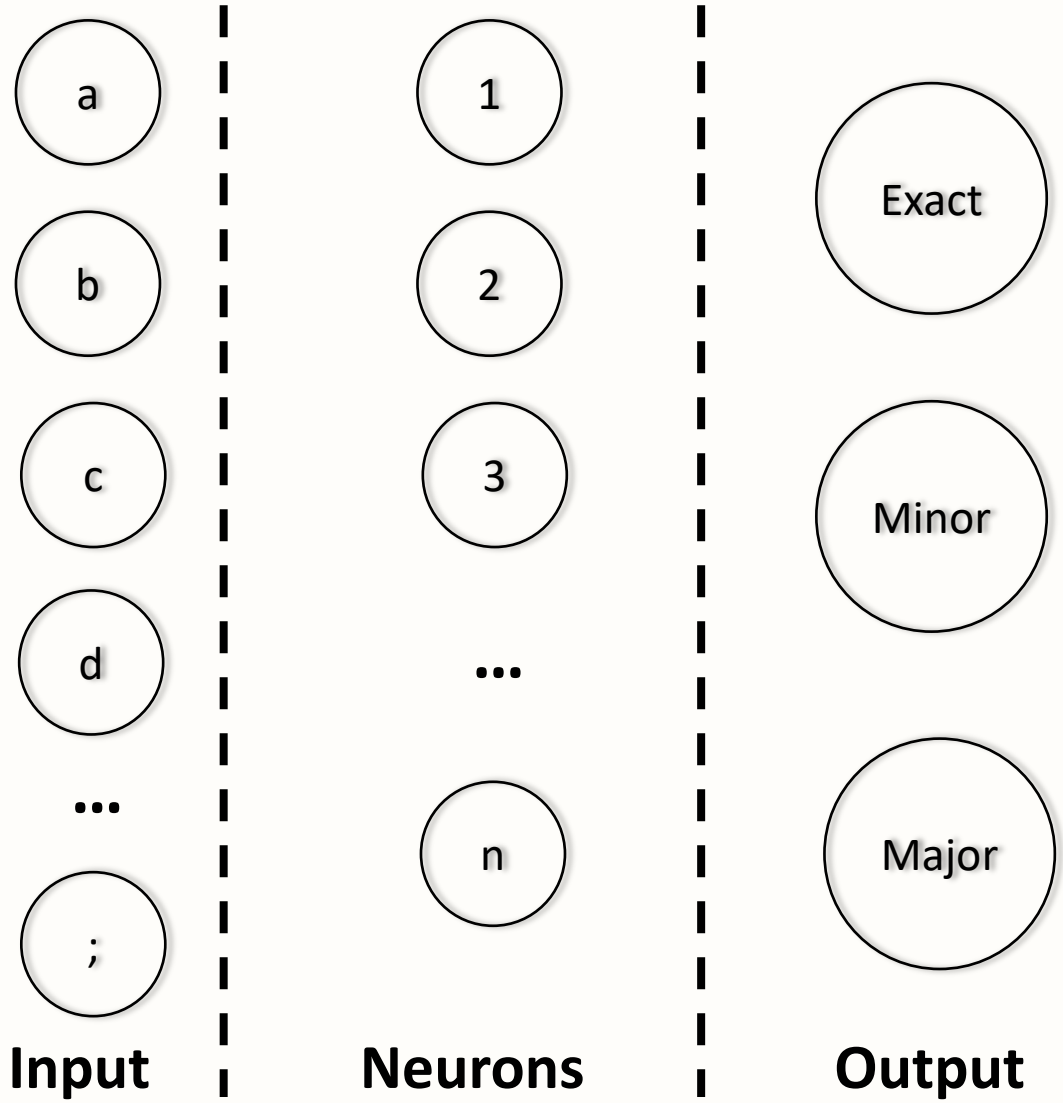
  - Common Process:
    - Training: Humans provide examples (e.g., transcripts) and their classifications (e.g., behavior codes) as input, computer discovers patterns
    - Validation: Given additional examples (e.g., transcripts), check overfitting
    - Test: Computer classifies new instances (e.g., new sets of transcripts) based on previous examples, compare accuracy to human classification



Methods for Identifying Deviations from Exact Reading

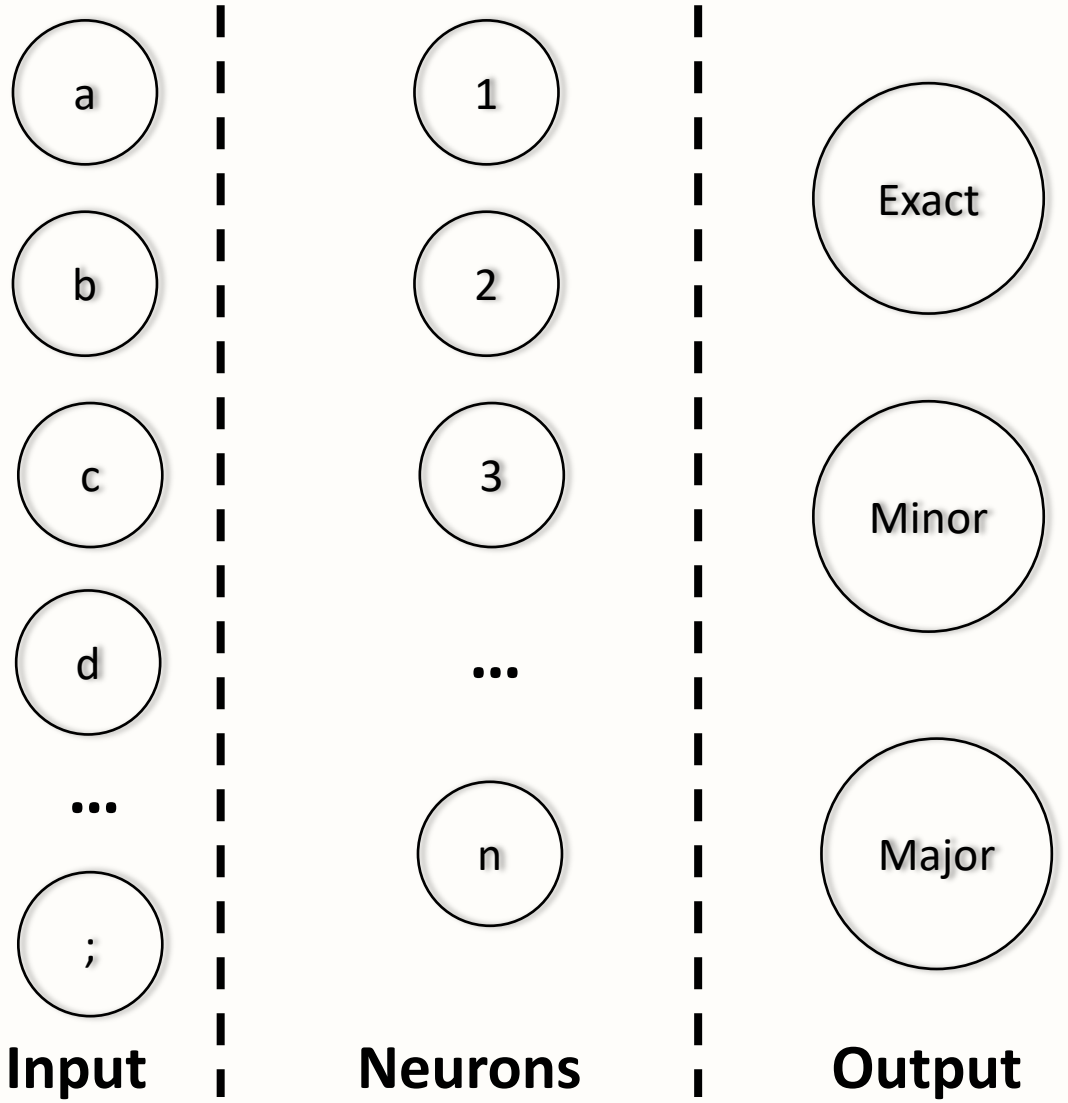
- **Machine Learning**
  - Recent Research Applications:
    - Coding how well therapists adhere to proper treatment methods using transcripts of clinical sessions (Xiao et al. 2016)
    - Coding news articles as relevant/irrelevant for content analysis (Nelson et al. 2018)
  - This project: Recurrent Neural Networks (RNNs)

Recurrent Neural Networks



Recurrent Neural Networks

and so, what is your sex?



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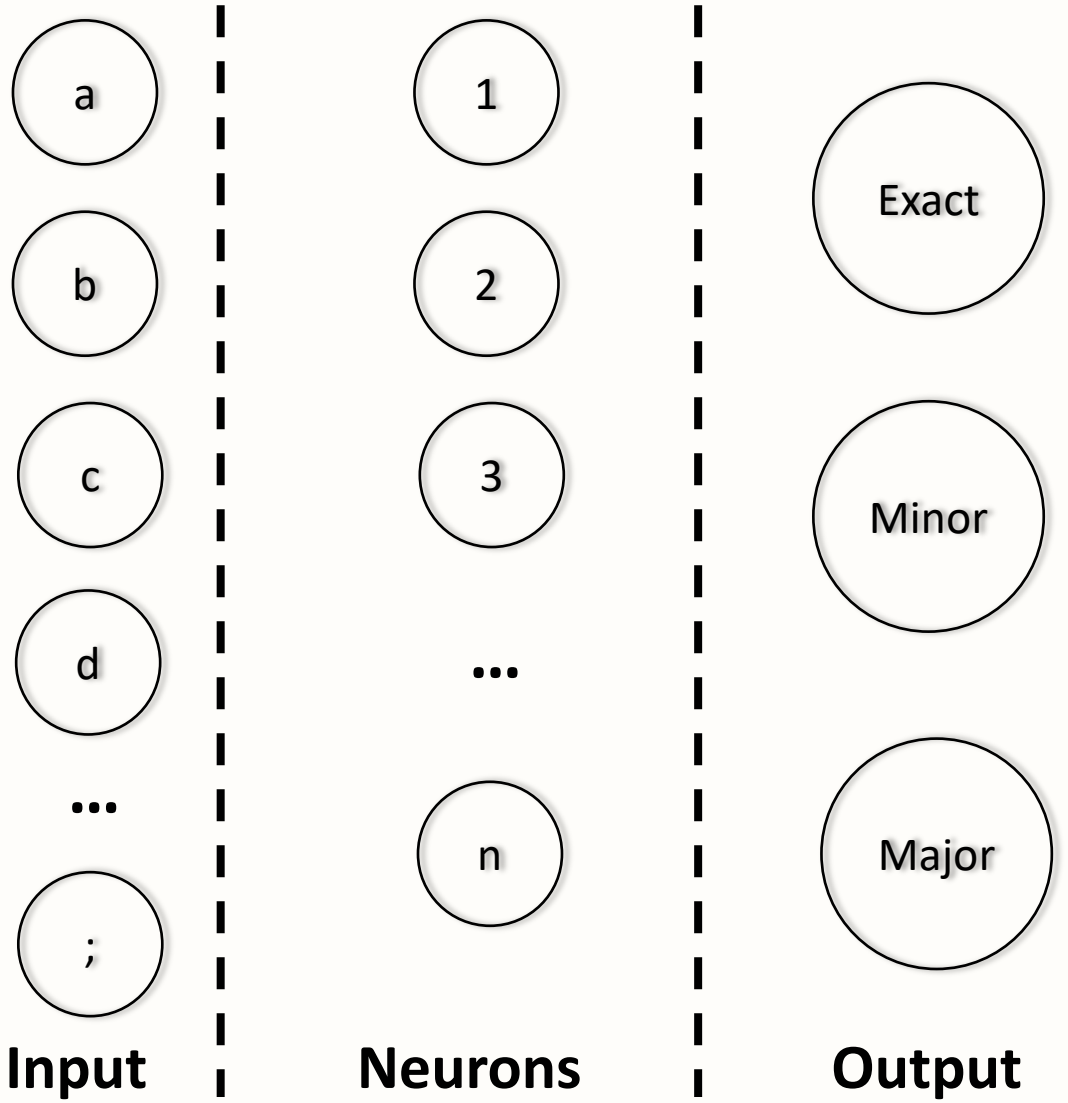

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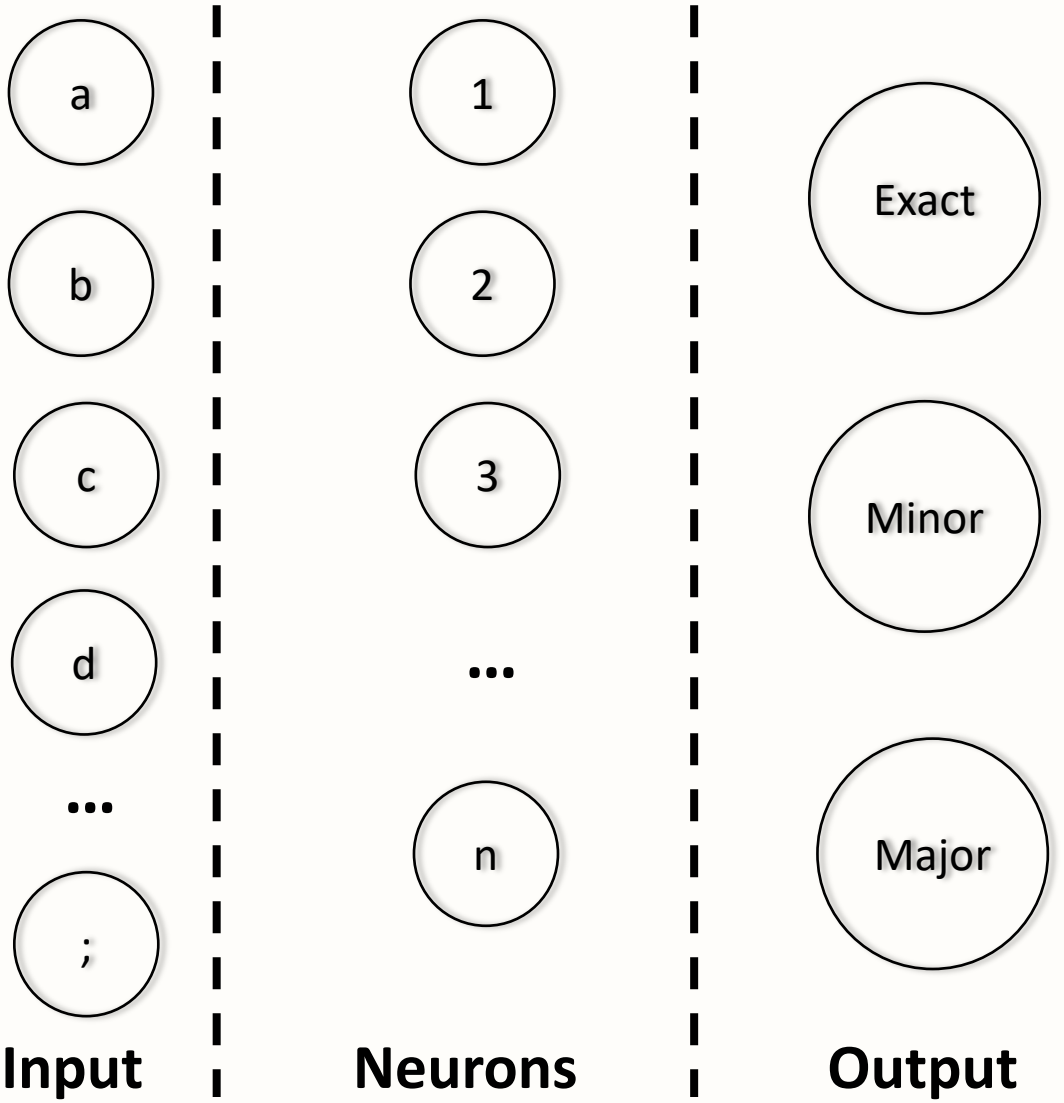

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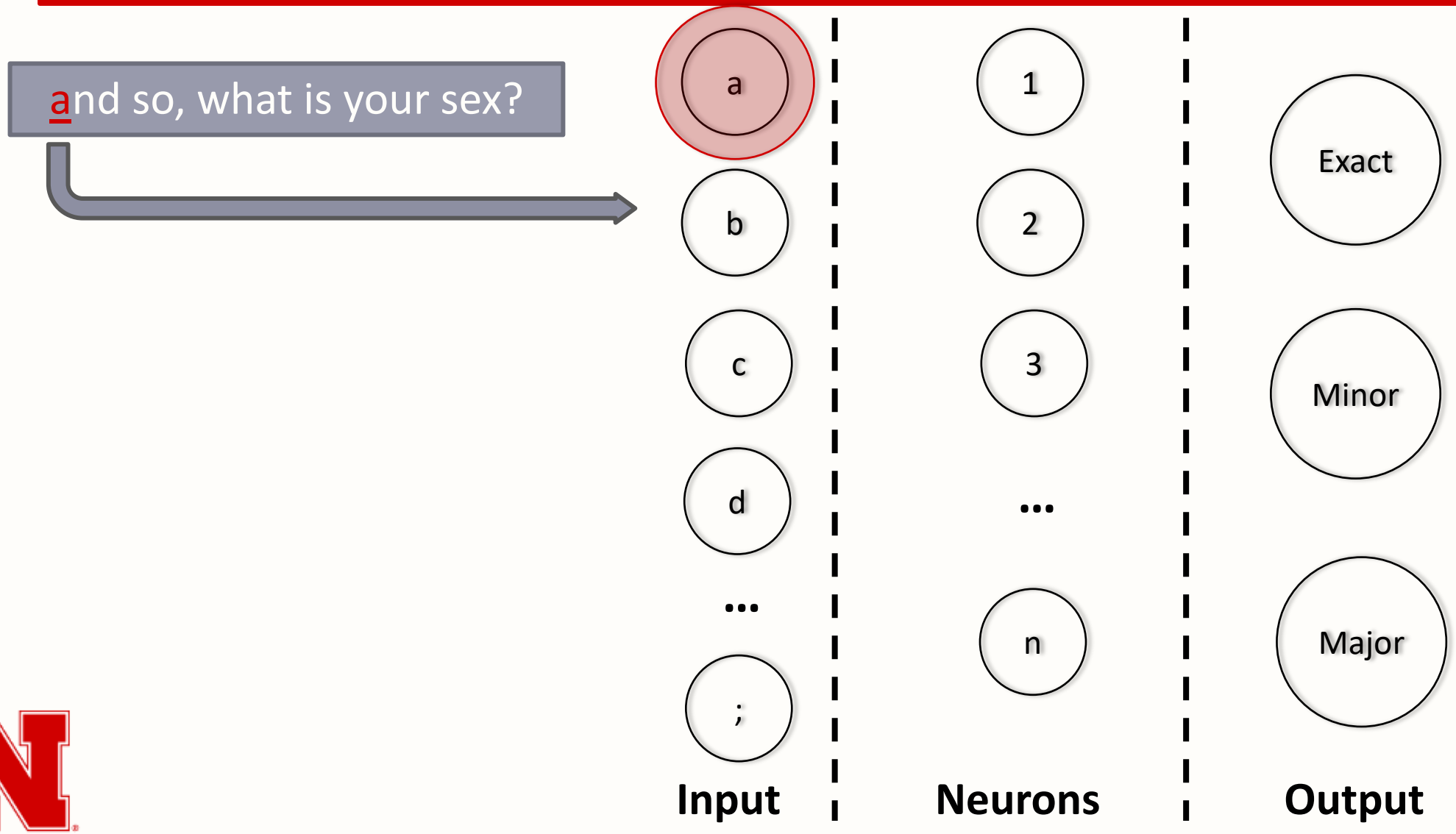

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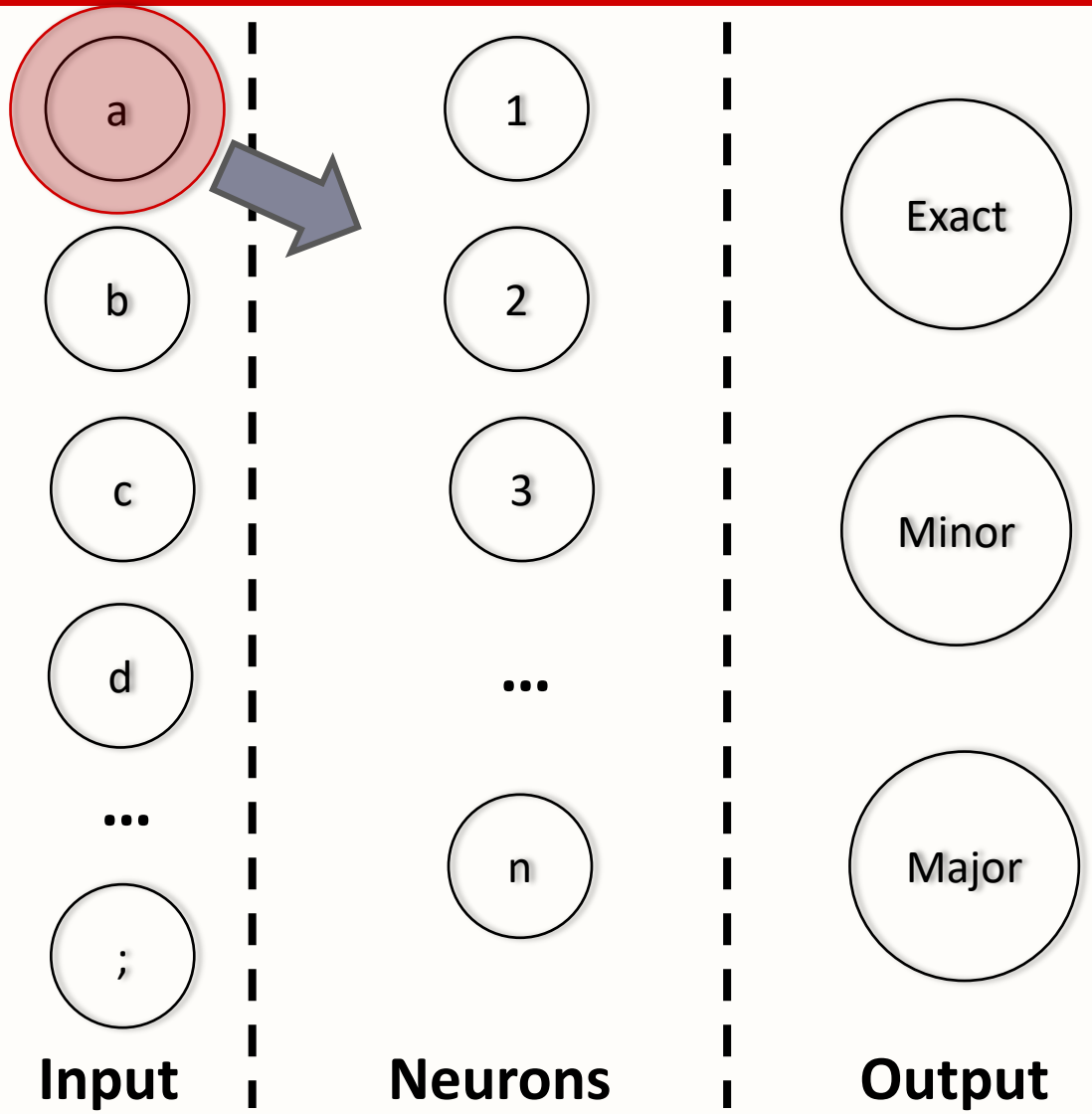

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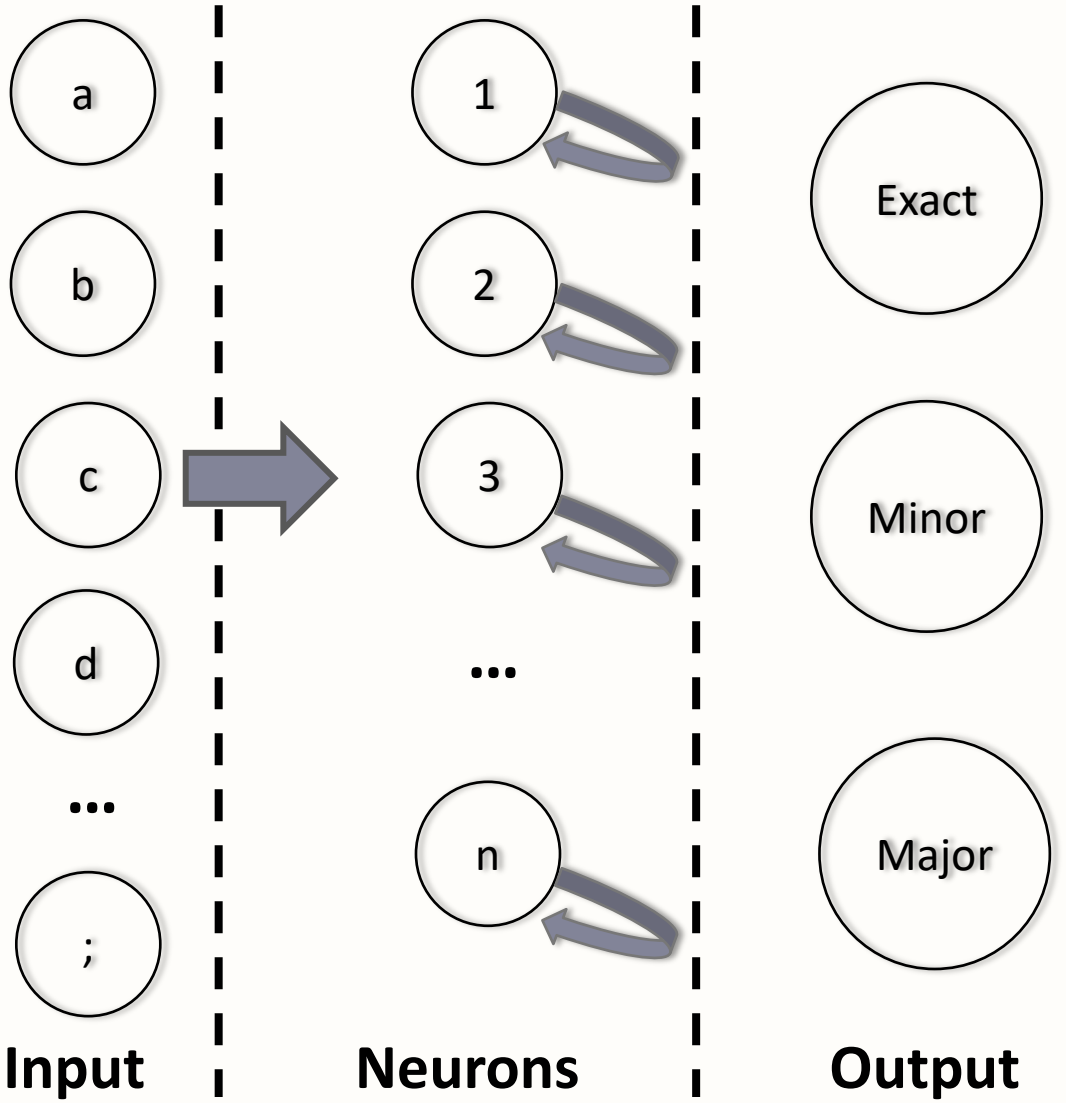

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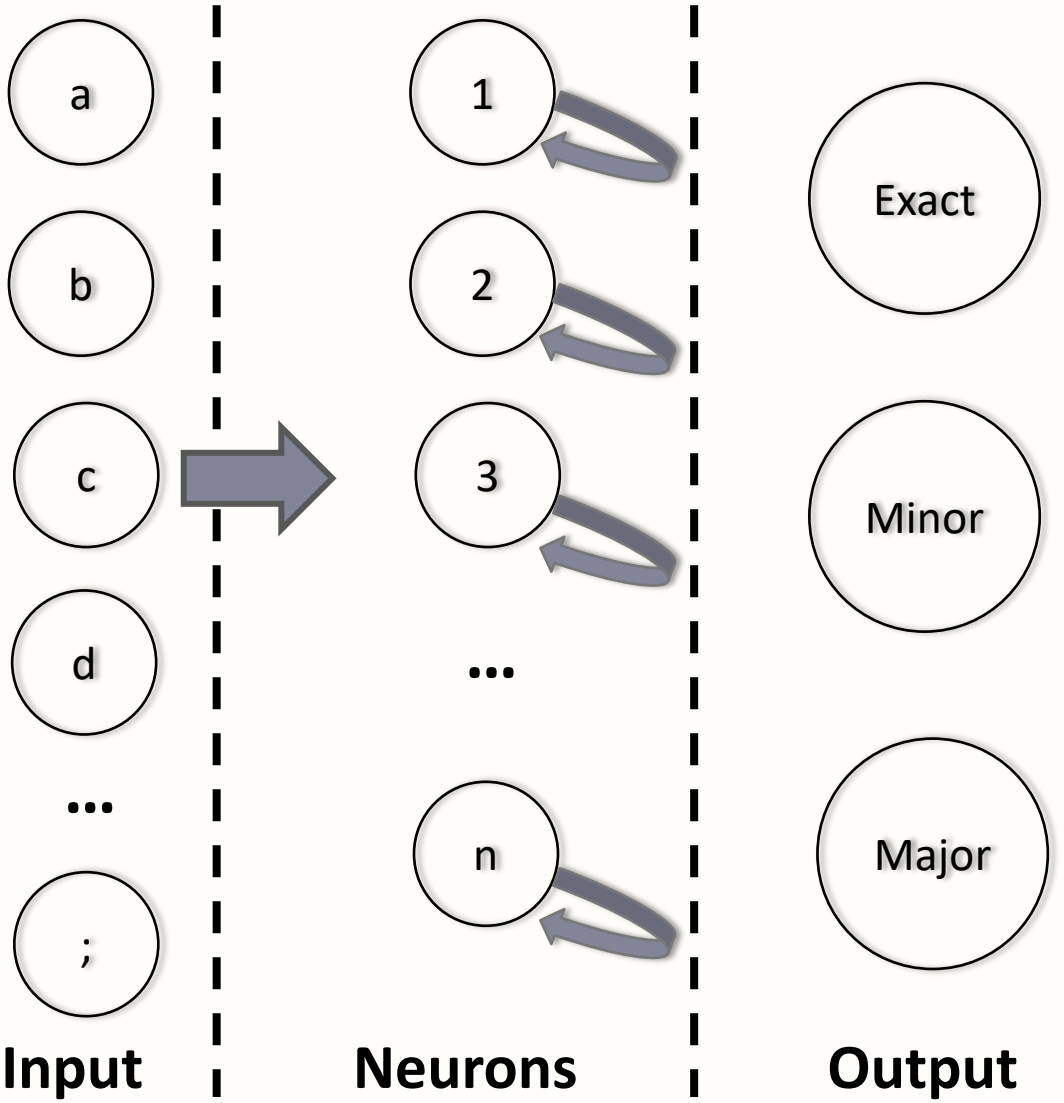

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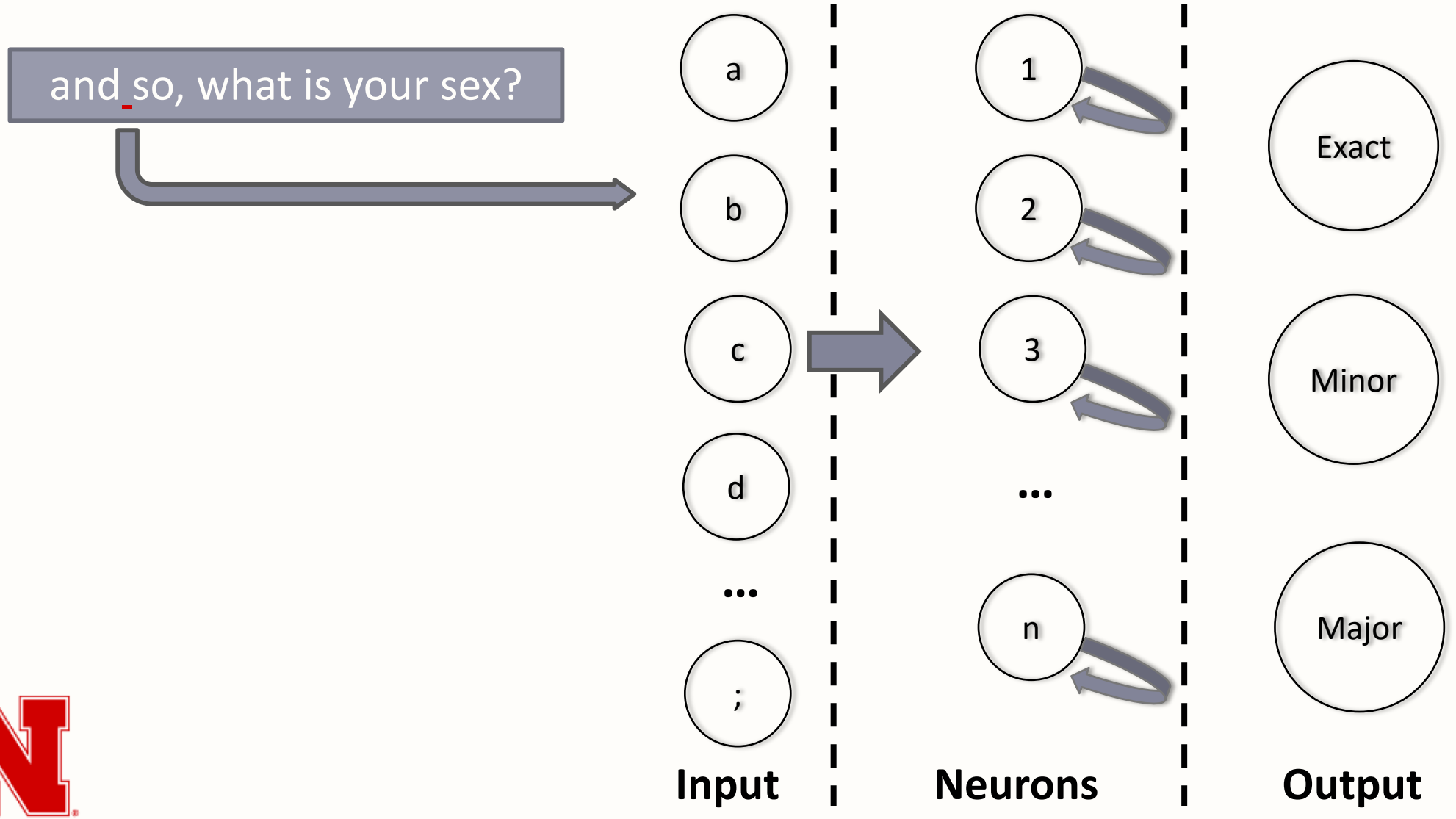

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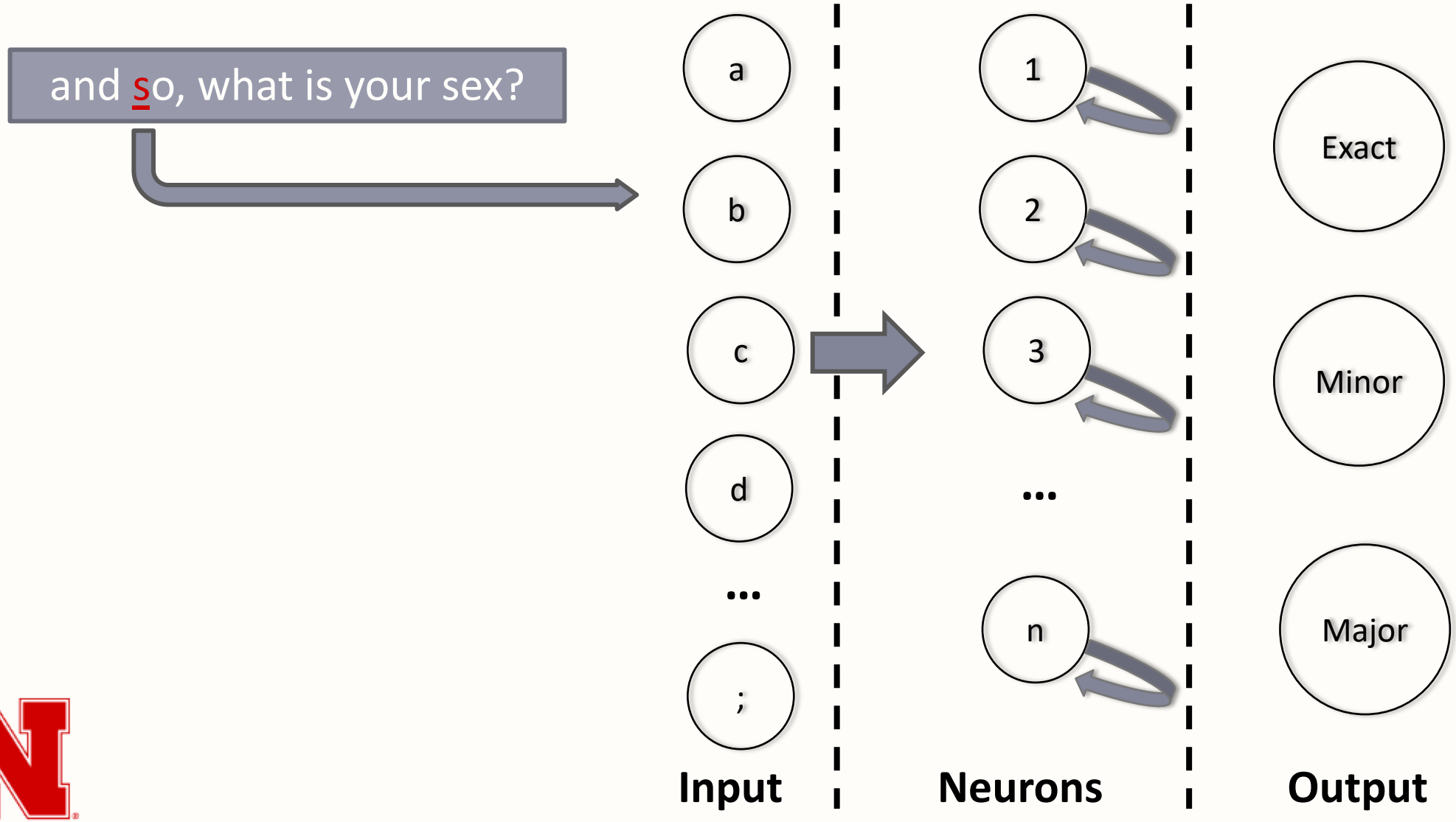

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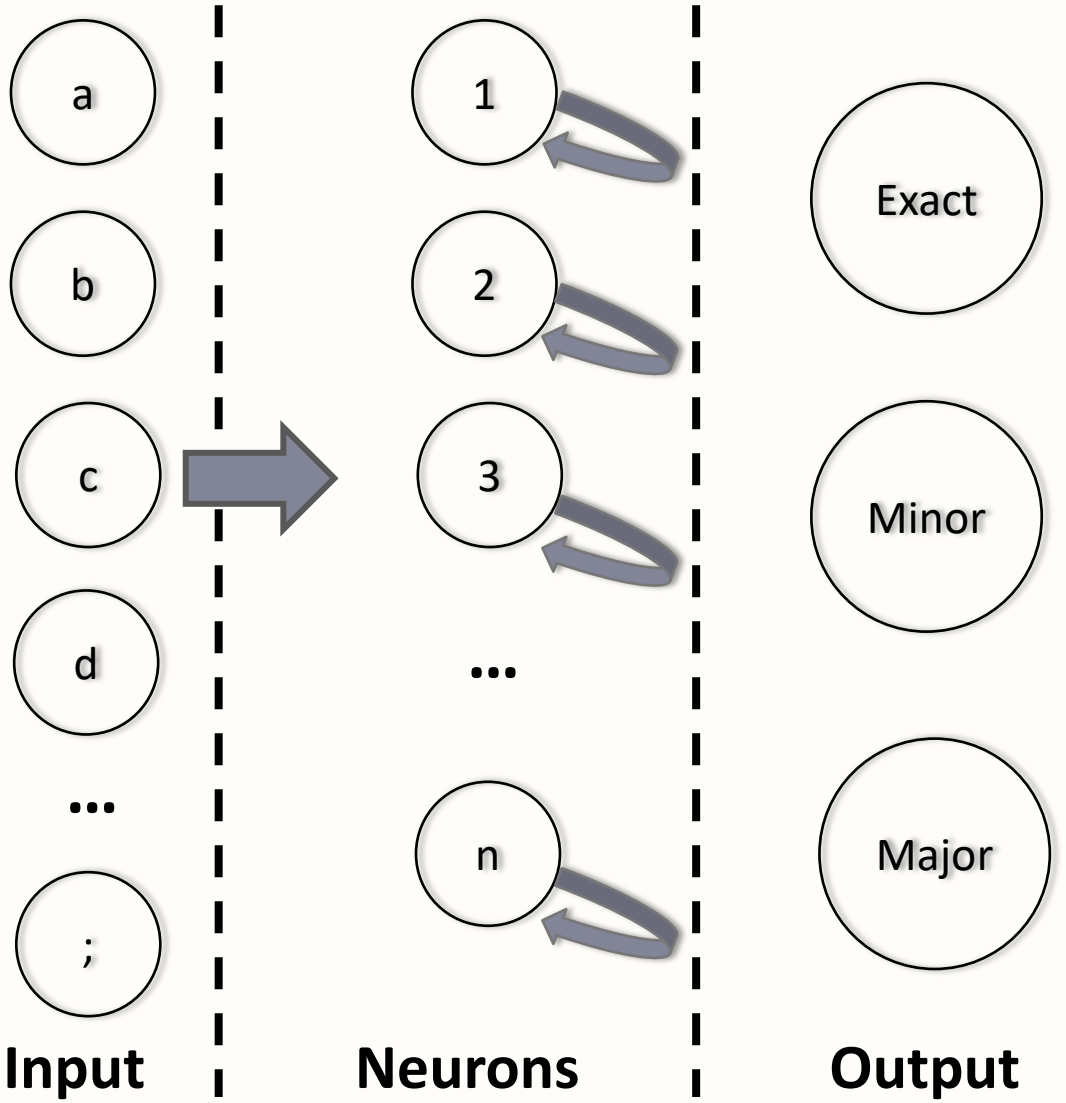

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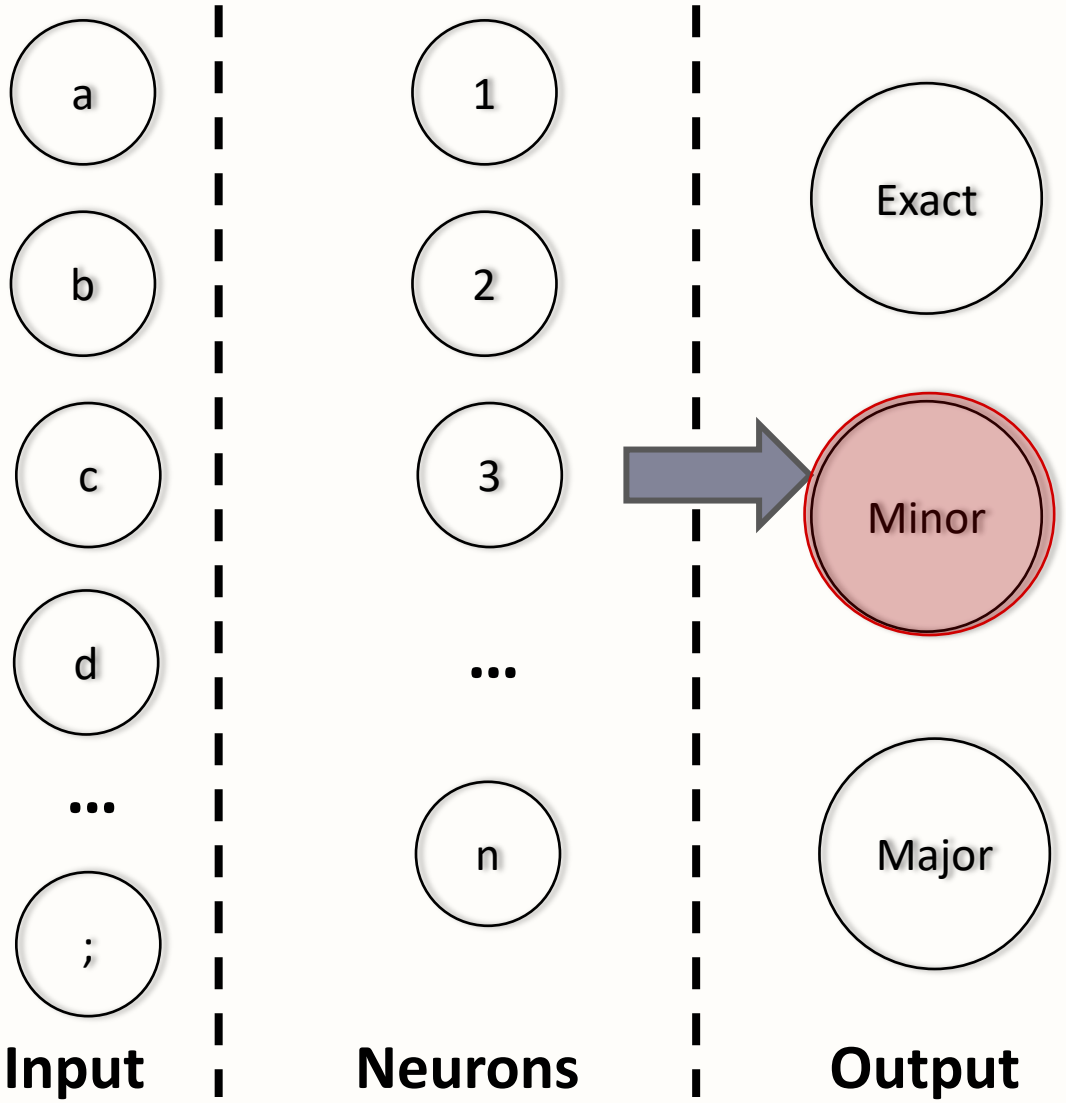
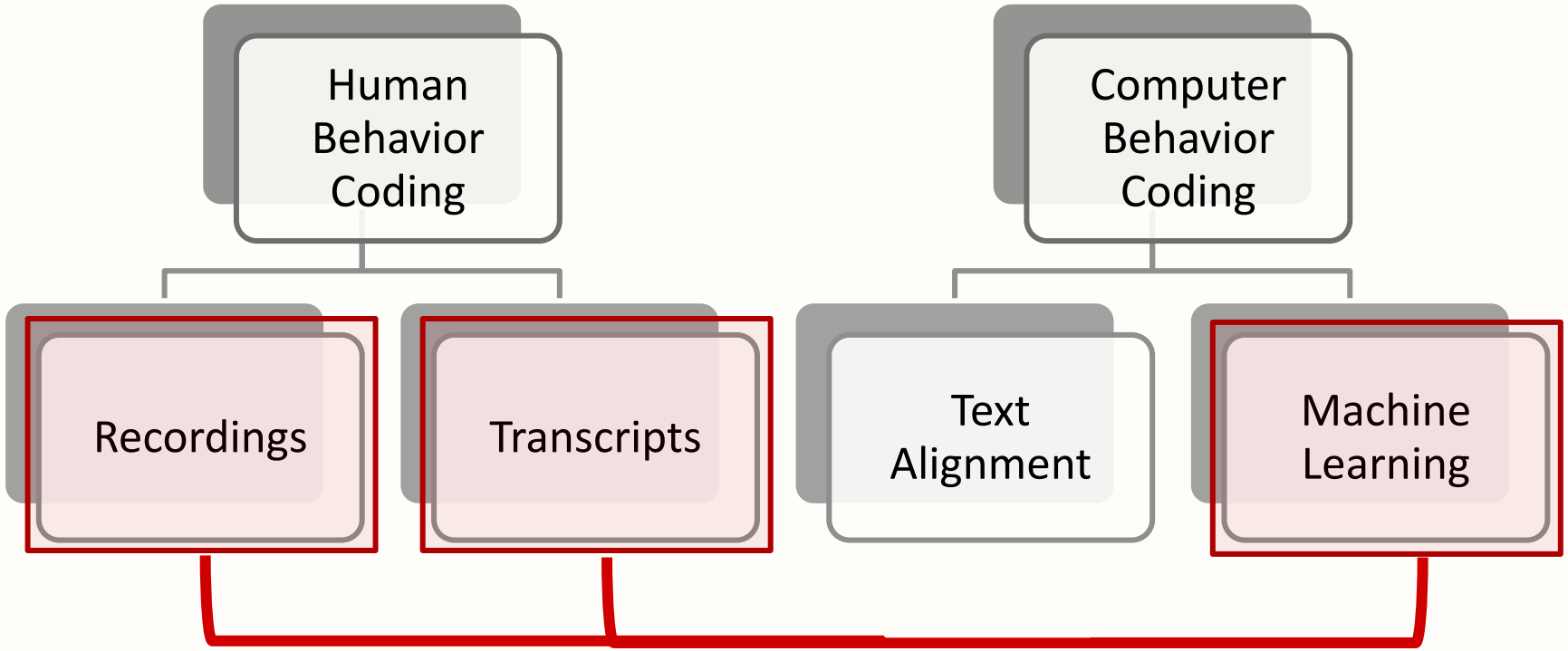


Recurrent Neural Networks (RNNs)

- **Pros**
  - Once a network is trained for a question, the “per case” cost does not increase
  - Accounts for the sequential nature of text data
    - Discovers the contextual importance of words (e.g., exact readings vs. major changes)
- **Cons**
  - Transcripts required for every case
  - Technical knowledge required
  - Computing power required

The Present Study



Research Questions

- **Can recurrent neural networks partially automate the coding of interviewer question-asking behaviors?**
  - Is the accuracy of RNN coding comparable to human coders?
  - Does the accuracy of RNN coding depend on having a high prevalence of each behavior in the training data?

Data

- **Work and Leisure Today 2 Survey**
  - National telephone survey of U.S. adults conducted by Abt SRBI in Aug and Sept of 2015.
  - Dual-Frame (Landline and Mobile)
  - n=902; AAPOR RR3 = 7.8%
  - 58 questions
  - All interviews were recorded and transcribed

Operationalizing Question-Asking Turns and the Outcome

- **Question-Asking Turns**
  - The interviewer's first conversational turn for each question
    - Conversational turn = uninterrupted speech by one actor
  - Excludes turns where:
    - The interviewer was interrupted by the respondent
    - The interviewer stuttered
- **Outcome variable**
  - Behavior Code assessing interviewer's question-asking
    - Exact Reading
    - Minor Change
    - Major Change

Questions Selected for Analysis

- **6 Questions selected for analysis**
  - 3 questions with a high prevalence of major/minor changes in training data

Question Topic	Question Type	% Exact Readings	% Minor Changes	% Major Changes
Respondent Sex	Demographic	64.7%	20.4%	14.9%
Leisure Activities	Open-Ended	80.5%	9.3%	10.2%
Access to Job Equipment	Attitude/Opinion	69.4%	14.8%	15.8%

Questions Selected for Analysis

- **6 Questions selected for analysis**
  - 3 questions with a low prevalence of major/minor changes in training data

Question Topic	Question Type	% Exact Readings	% Minor Changes	% Major Changes
# Adults in HH	Demographic	85.7%	11.8%	2.5%
Threats to Personal Privacy	Open-Ended	90.4%	4.0%	5.6%
Own Cell or Smartphone	Frame	72.4%	25.7%	1.9%

Human Coding

- **Undergrad-Coded Data**
  - 16 undergraduate students
  - Coded question-asking behaviors for 899 interviews
    - 45,078 question-asking turns
  - Used Sequence Viewer software (Dijkstra 1999)
    - Allows coders to read and hear question-asking
- **Master-Coded Data (Ground Truthing)**
  - A 10% random subsample of the all data (94 cases, 4,688 question-asking turns)

Recurrent Neural Network Coding

- **Network Creation (for each question)**
  - Training Data (80% of undergrad-coded data)
    - Random subsample of the data
  - Validation Data (20% of undergrad-coded data)
    - Ensures model does not overfit data
  - k-fold cross-validation for each question
    - *k*=5 different networks with *k*=5 different subsamples per question
      - Most accurate network on validation method retained
      - Minimize selection of a “bad” training set
- **Testing Data (100% of master-coded data)**
  - Cases not used for training or validation

Analyses

- **Kappa Scores**
  - Calculated by question between:
    - Undergrad coders and master coders
    - RNN coding and master coders
  - Test for differences in kappas across undergrads and RNNs by question:
    - Bootstrapped 95% confidence intervals (*B*=500)
    - Non-overlapping CI's as statistically significantly different

Analyses

- **Percent Agreement / Accuracy by Question**
  - An alternative to kappa for rare events (Viera & Garrett 2005)
  - $\frac{\#\ of\ correct\ predictions}{Total\ \#\ of\ predictions}$

- **Recall**
  - For each behavior, what proportion of master-coder identified behaviors (i.e., exact reading, minor change, or major change) was identified by the RNN or the undergrad coders?
  - $\text{Recall}_{minor} = \frac{\#\ of\ times\ RNN\ AND\ master\ coder\ identified\ a\ minor\ change}{\#\ of\ times\ master\ coder\ identified\ a\ minor\ change}$

Results – Kappas and % Agreement / Accuracy

- **<u>High Prevalence</u> of Major/Minor Changes**

Results – Kappas and % Agreement / Accuracy

- **High Prevalence of Major/Minor Changes**

Question Topic	Question Type	Kappa with Master Coder				% Agree / Accuracy with Master Coders		
		Undergrad	RNN	Diff		Undergrad	RNN	Diff
Respondent Sex	Demographic	0.39	0.47	-0.08		61.73%	65.88%	-4.15%
Leisure Activities	Open-Ended	0.60	0.57	0.03		84.52%	82.76%	1.76%
Access to Job Equipment	Attitude/Opinion	0.70	0.80	-0.10		85.71%	90.48%	-4.77%

*p<.05

Results - Recall

- **High Prevalence of Major/Minor Changes**

Question Topic	Question Type	Exact Reading			Minor Change			Major Change	
		Undergrad	RNN		Undergrad	RNN		Undergrad	RNN
Respondent Sex	Demographic	80.55%	94.44%		29.63%	16.67%		72.22%	89.47%
Leisure Activities	Open-Ended	100.00%	98.36%		21.43%	13.33%		81.82%	90.09%
Access to Job Equipment	Attitude/Opinion	96.55%	100.00%		50.00%	50.00%		80.00%	100.00%

$$\text{Recall}_{minor} = \frac{\#\ of\ times\ RNN\ AND\ master\ coder\ identified\ a\ minor\ change}{\#\ of\ times\ master\ coder\ identified\ a\ minor\ change}$$

Results – Kappas and % Agreement / Accuracy

- **Low Prevalence of Major/Minor Changes**

Question Topic	Question Type	Kappa with Master Coder				% Agree / Accuracy with Master Coders		
		Undergrad	RNN	Diff		Undergrad	RNN	Diff
# Adults in HH	Demographic	0.20	-0.02	0.22*		73.47%	67.31%	6.16%
Threats to Personal Privacy	Open-Ended	0.80	0.55	0.25		95.29%	89.77%	5.52%
Own Cell or Smartphone	Frame	0.38	0.11	0.27*		63.64%	45.68%	17.96%

*p<.05

Results - Recall

- **Low Prevalence of Major/Minor Changes**

Question Topic	Question Type	Exact Reading			Minor Change			Major Change	
		Undergrad	RNN		Undergrad	RNN		Undergrad	RNN
# Adults in HH	Demographic	100.00%	97.22%		14.28%	0.00%		100.00%	0.00%
Threats to Personal Privacy	Open-Ended	98.65%	98.67%		83.33%	12.50%		60.00%	80.00%
Own Cell or Smartphone	Frame	96.30%	89.29%		48.89%	26.09%		20.00%	0.00%

$$\text{Recall}_{minor} = \frac{\#\ of\ times\ RNN\ AND\ master\ coder\ identified\ a\ minor\ change}{\#\ of\ times\ master\ coder\ identified\ a\ minor\ change}$$

Summary of Findings

- **RNN-coding is comparable to undergrad coding when there is a *high prevalence* of deviations from exact reading in the training data**
  - More deviations to train on = RNN coding comparable to undergrads
- **RNN-coding performs worse than undergrad coding when there is a *low prevalence* of deviations from exact reading in the training data**
  - Fewer deviations to train on = worse RNN coding
- **RNN-coding has trouble identifying minor changes**
  - But minor changes do not affect question meaning, and may not be of interest for most researchers.

Limitations and Future Directions

- **Many opportunities to refine RNN model**
  - Collapsing Exact Readings and Minor Changes
  - Change RNN parameters to change performance (e.g., # of hidden neurons, layers, learning rate)
  - Minimum amount of training data required to produce results comparable to undergrads
- **More behaviors!**
- **Refining training/validation/test sources**
  - Mixing undergrad- and master-coded data into training/validation?

Final Takeaway

- **RNNs are a promising method for automating behavior coding of interviewer question-reading behaviors, especially when many major changes are expected.**
  - More results after more optimization!

Thank you!

Contact:
Jerry Timbrook
jerry.timbrook@gmail.com