Towards an Automatic Approach for Assessing Program Competencies

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Motivation

- Skills analysis in economics, education, policy making
  – Understanding economic needs
  – Observing and forecasting skill trends
  – Aligning industry needs and training
  – Developing re-skilling programs
  – Ministries push towards competency based education

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  - Fast-changing skills
  - Role in developing scalable solutions
- Our goal: To develop scalable approach for evaluating program competencies
  - Develop automatic skills extraction system
  - Identify skill gaps in a CS program

Related Work

- Definition of “skill” [Green 2013;Payne 2017; Duckworth & Yaeger 2015]
  - Cognitive and non-cognitive abilities
  - Emotional abilities
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- Skill assessments [Rios et al. 2020]
  - Self-reported questionnaires, employer surveys
  - Teacher/observer reports
  - Performance tasks, job analysis data
  - Expert theoretical synthesis

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  - Performance tasks, job analysis data
  - Expert theoretical synthesis
- Major approaches in skills analysis with labor market data (cf. paper)
  - Content analysis coded by domain experts
  - Automatic approach using keyword matching
  - Domain and language knowledge via external resources
  - Machine learning algorithms for generalizability

Job Skills Landscape

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- Aligning supply of skills with demand for employment [McGuinness et al. 2018]
- Changing skills in IT
  - Across time [Todd et al. 1995; Smith & Ali 2014]
  - Across career stages [Kappelman et al. 2016]
  - Across company size [Nelson et al. 2007]

Skill Gaps in CS Education

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- Impact within on curriculum [Patacsil & Tablatin 2017; Radermacher et al. 2014;Börner et al. 2018; Restuccia 2019]
  - Gap in student skills and industry needs
  - CS: Prioritization in communication, testing, project experience, problem-solving in practical settings, specialized tools
  - Börner et al. used keyword matching to extract longest matching skill from publication abstracts, course syllabi, job postings

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  - Specialized track in TREC (2005+) focus on expert search
  - LinkedIn [Skomoroch et al. 2012]: deep NLP analyses, clustering, crowdsourcing
  - SKILL by CareerBuilder [Hoang et al 2015;Javed et al. 2017;Zhao et al. 2015]: skills taxonomy generation, deep NLP analyses, Wikipedia categories
  - ScholarLens [Sateli et al. 2017]: extract competencies from publications to create researcher profiles
  - Others [Bernabé-Moreno 2019; González-Eras & Aguilar 2019]: linguistic phrase structure, additional resources, clustering

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- Classification of job skills
  - Skills database to explore employee turnover [Liu et al 2018]
  - WoLMIS [Boselli et al. 2018] classified job ads to occupational codes

Our Methodology

- No fixed keywords or strict text format requirement
- Major steps:
  - Seed phrases
  - Preprocessing
  - Linguistic patterns analysis
  - ML text classification models
  - Evaluation

Our Methodology

- Seed phrases
  - Research database edgemap.ok.ubc.ca with 202 students in Digital Citizenship course self-reported 1,966 skills
  - Manually extracted skills from 1,700 job postings from indeed.com
  - Intercoder reliability (1st: 82%, 2nd: 94% agreement)
  - Result: 6,972 phrases with 4,886 skills and 2,086 non-skills
- Preprocessing
- Linguistic patterns analysis
- ML text classification models
- Evaluation

Our Methodology

- Seed phrases
- Preprocessing
  - Standard NLP steps to process job description sections
  - Removed HTML tags, tokenization by punctuation and conjunctions, removed stop words, lemmatization, POS tagging
- Linguistic patterns analysis
- ML text classification models
- Evaluation

Our Methodology

- Seed phrases
- Preprocessing
- Linguistic patterns analysis

Linguistic Pattern	Examples
Noun phrase	Java, Microsoft Word, time management, strong programming skills
Verb/Gerund + Noun phrase	programming websites, design user interfaces
Noun phrase + Gerund	server hosting, software testing

- ML text classification models
- Evaluation

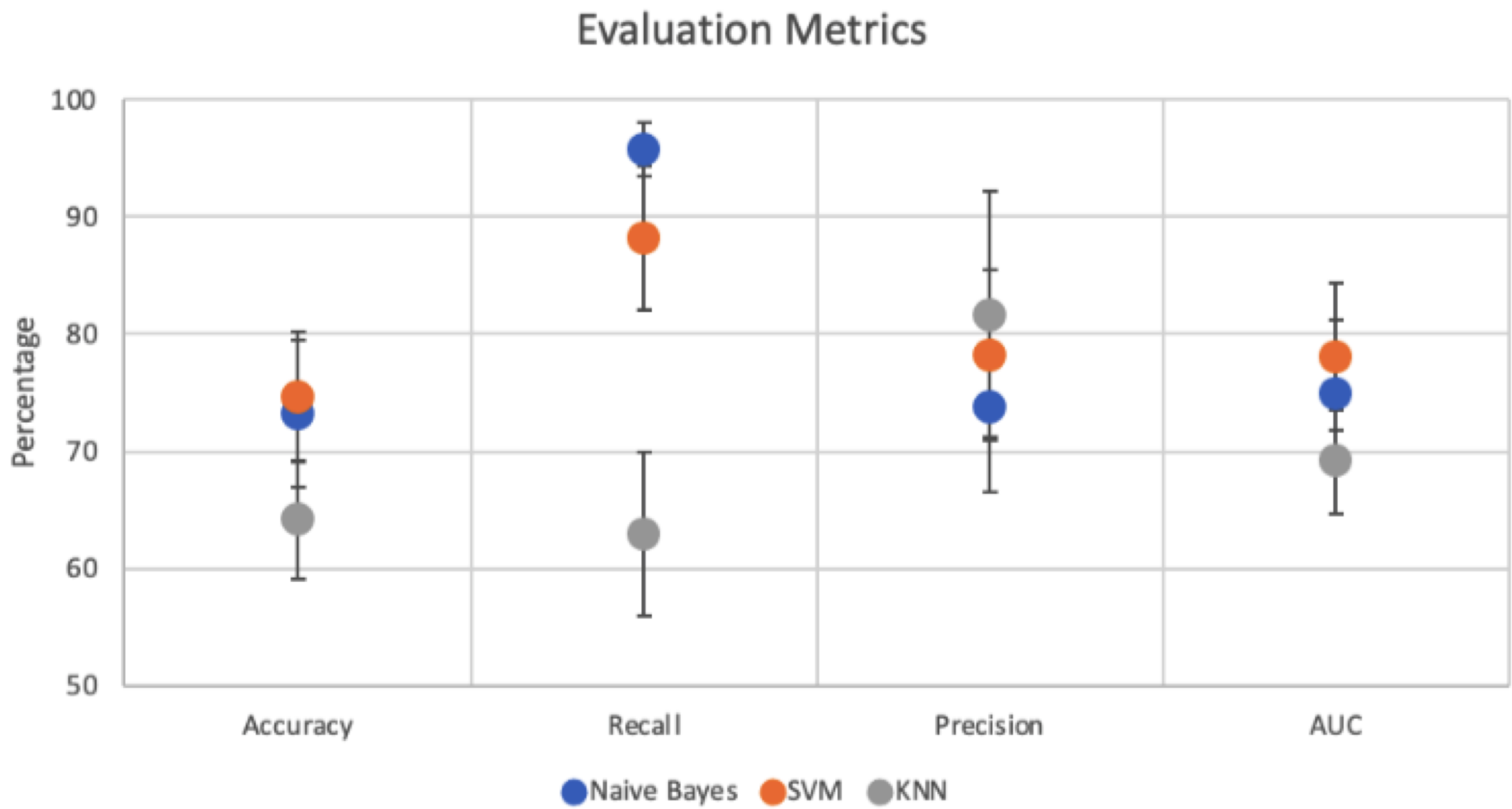
Our Methodology

- Seed phrases
- Preprocessing
- Linguistic patterns analysis
- ML text classification models
  - Used seed phrases as a labeled dataset for text classification
  - Extracted all linguistic patterns from job postings
  - Text classification models: Naïve Bayes, SVM linear, k-NN
- Evaluation

Our Methodology

- Seed phrases
- Preprocessing
- Linguistic patterns analysis
- ML text classification models
- Evaluation
  - 10-fold cross validation
  - Measured accuracy, recall, precision, AUC

Text Classification Performance



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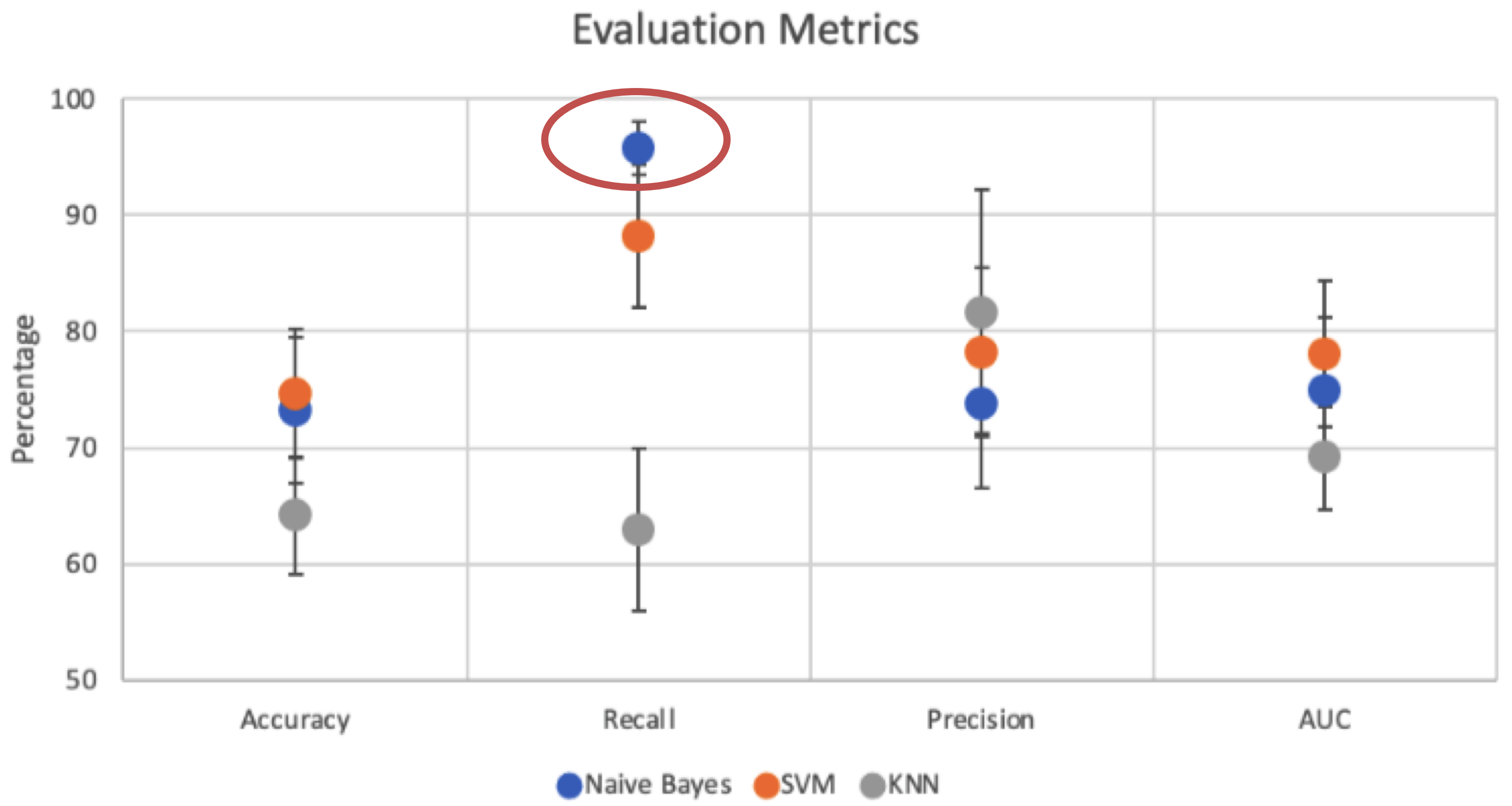

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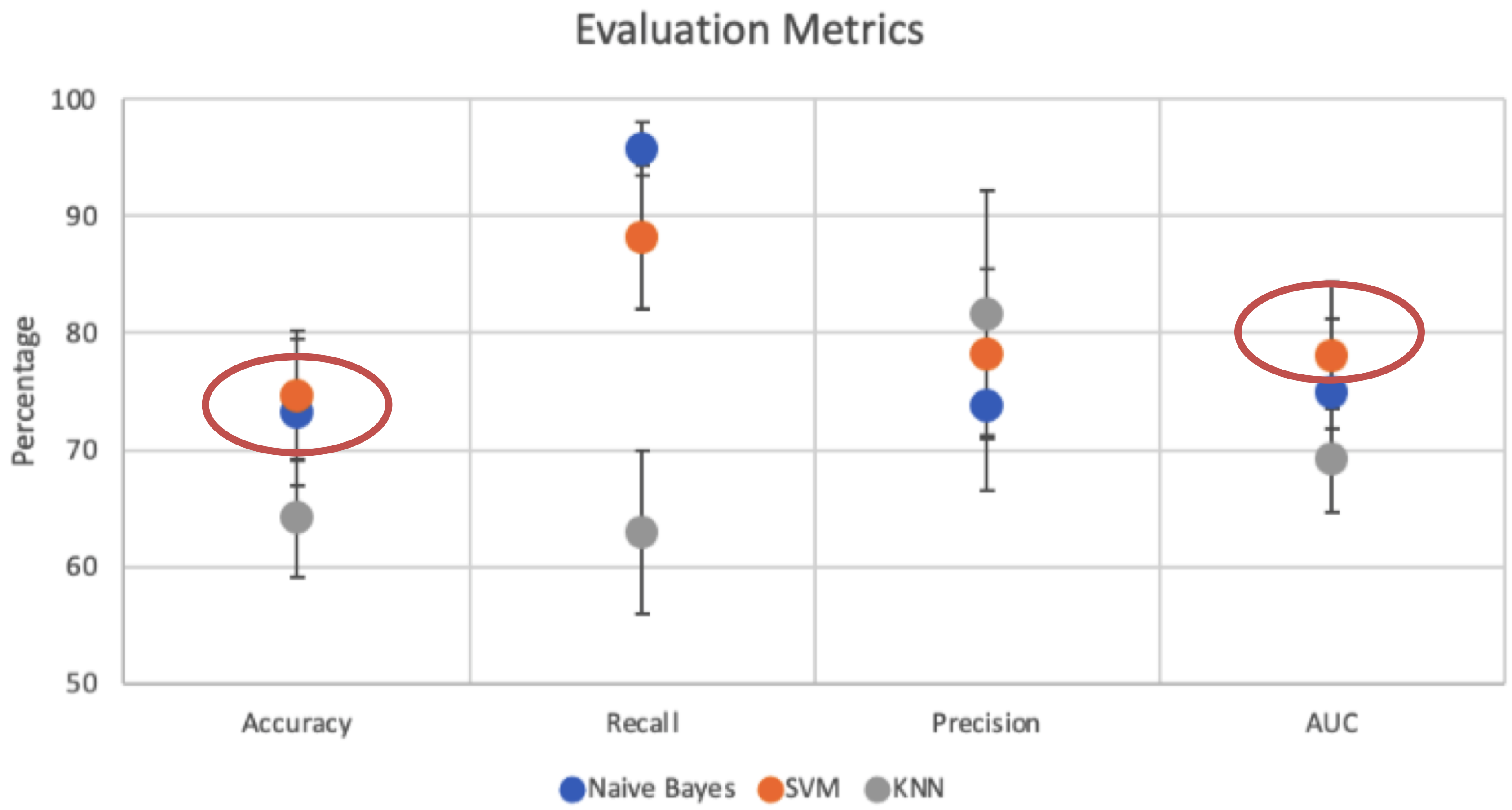

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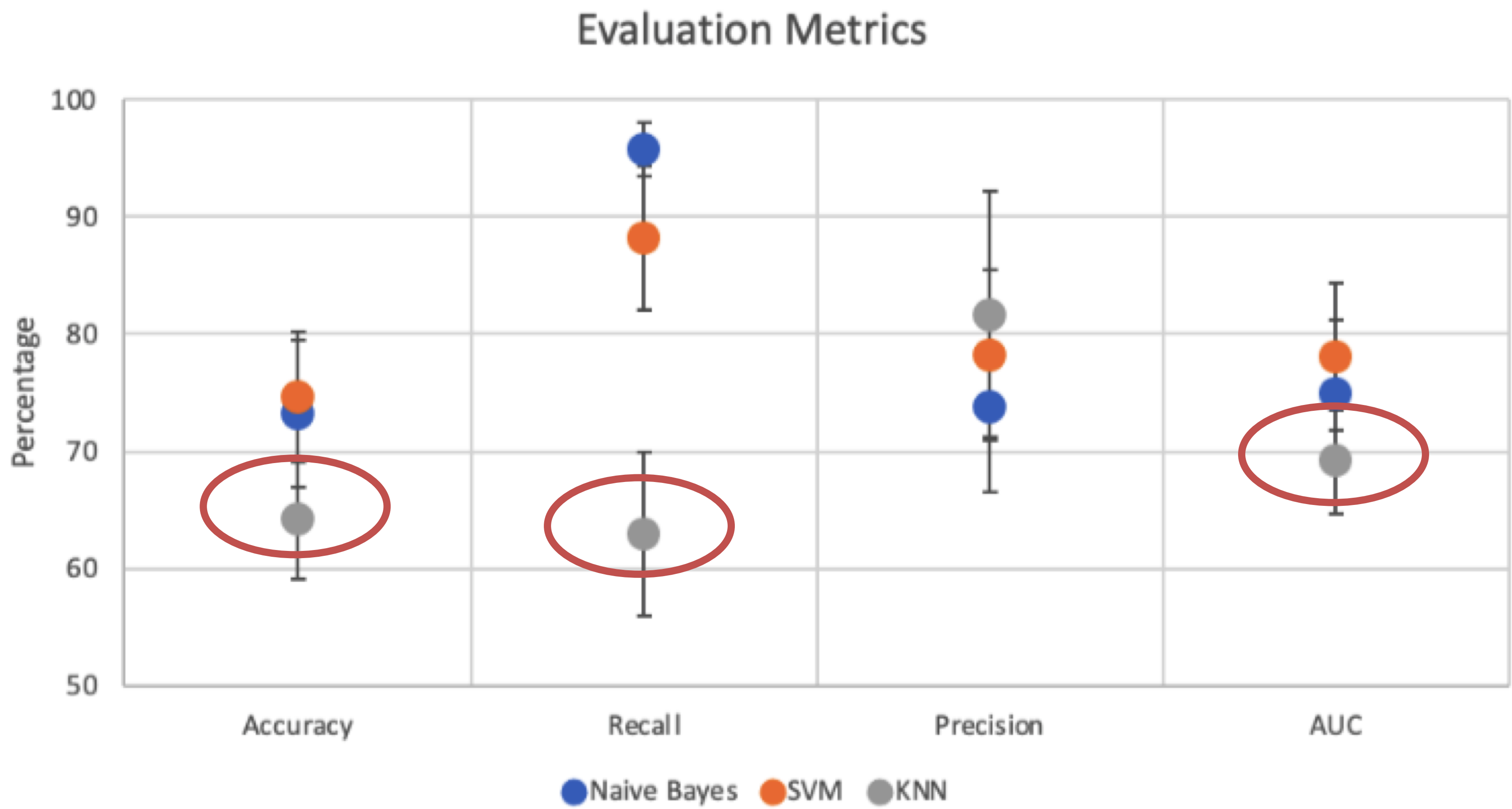

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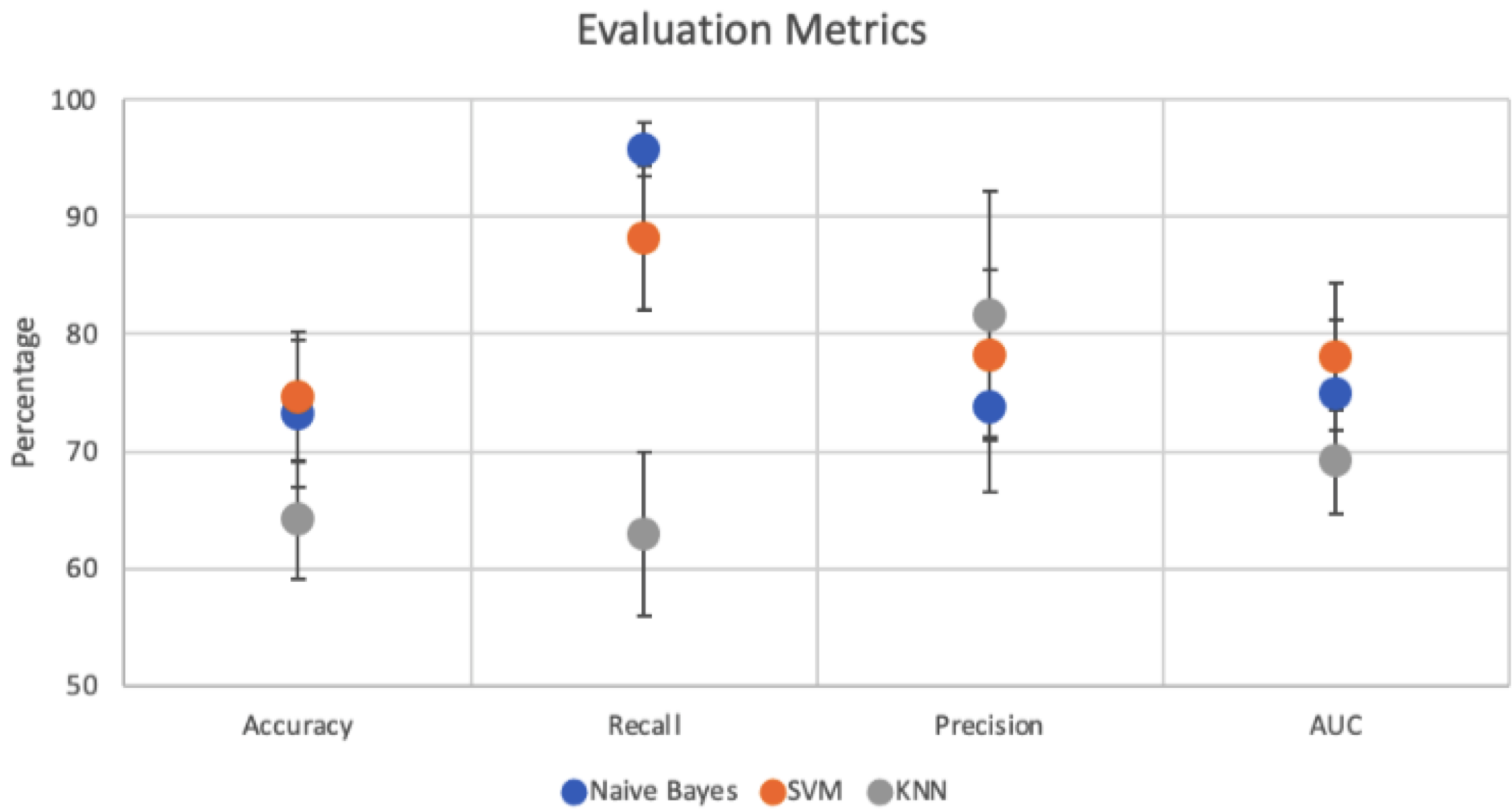
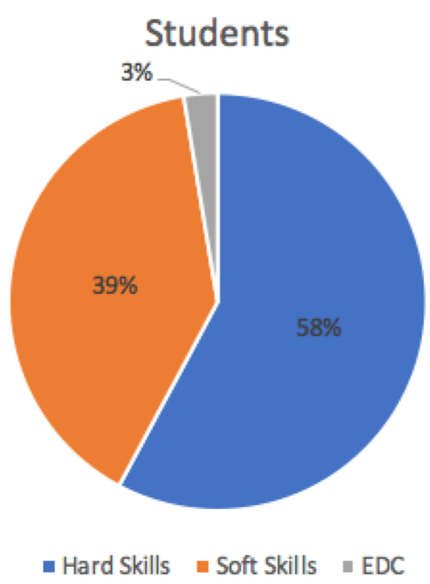


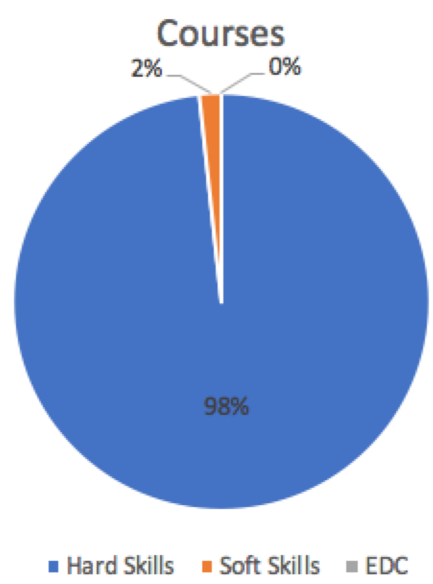
Analysis of Student Skills, University Courses, and Jobs

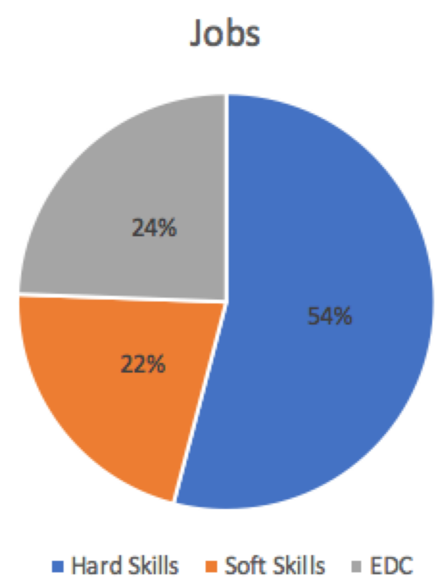
- Cross-sector perspective across 20 NAICS sectors
- CS discipline case study

Analysis of Student Skills, University Courses, and Jobs

- Cross-sector perspective across 20 NAICS sectors
- CS discipline case study
  - 202 students with 1,966 skills
  - 26 course syllabi in a CS program
  - 13,493 software developer job ads







High-Level Findings

- Software developer jobs demand mostly technical skills
- CS programs should incorporate more soft skills
- Students have a high proportion of soft skills

- Questions remaining:
  - Do students have the soft skills that jobs need?
  - Are courses teaching the hard skills that jobs need?

Comparing Overlaps in Skills

- How much overlap is there between the skills in each category?
  - KL-divergence to measure entropy between two distributions
    - KL=0: Identical skill sets
    - Higher KL: No overlap

Hard Skills	Students	Courses	Jobs
Students	0	0.5703	0.6967
Courses	0.2620	0	0.5730
Jobs	0.5137	0.3562	0

EDC	Students	Courses	Jobs
Students	0		0.0435
Courses		0	
Jobs	0.0383		0

Soft Skills	Students	Courses	Jobs
Students	0	0.1043	0.6288
Courses	0.1389	0	0.1253
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TOTAL	Students	Courses	Jobs
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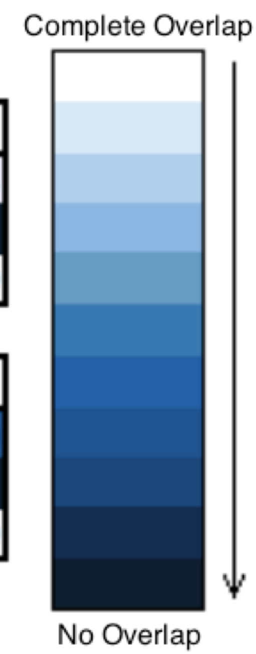

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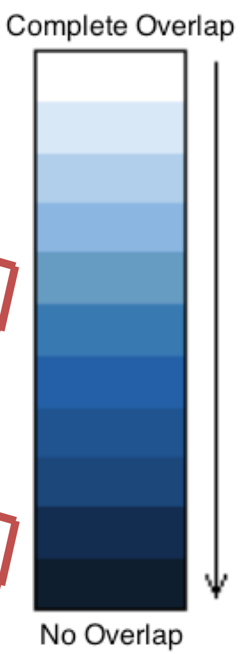

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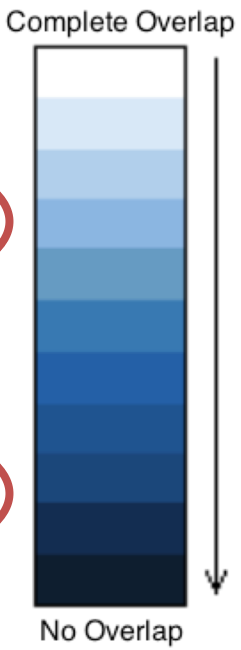

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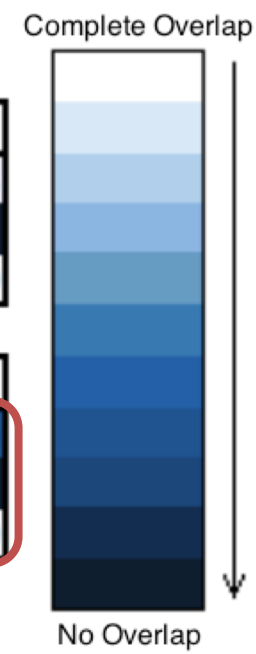

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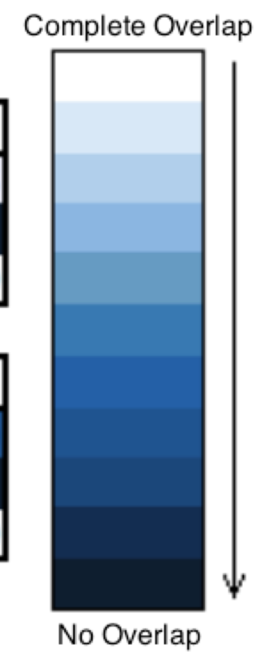

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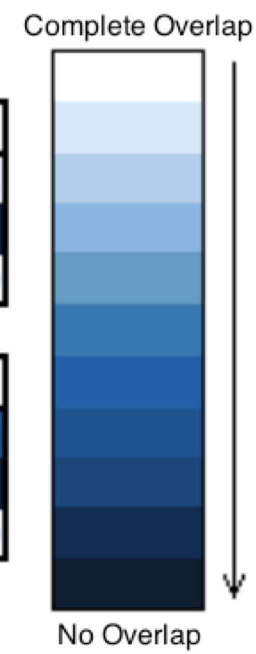

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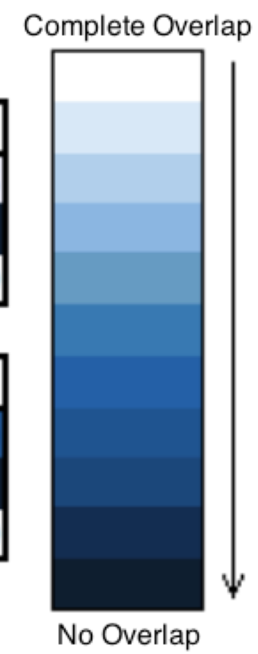
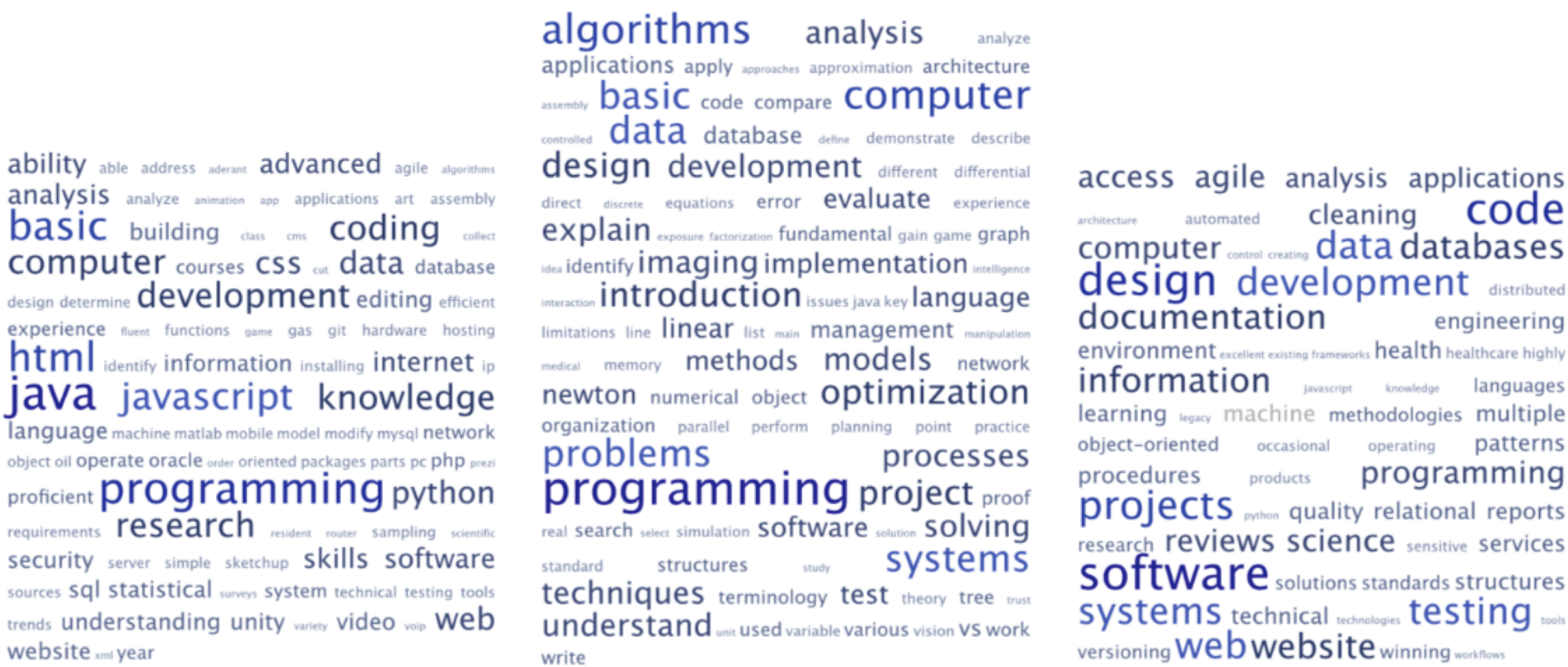


A Visual Comparison



(a) Students (b) Courses (c) Jobs

Conclusions and Future Work

- Summary contributions and findings
  - Auto-extract skills to analyze student skills, course syllabi, job postings
  - Within-sector analysis on programming jobs and training provided curricular insights on CS program
- Limitations
- Next steps

Conclusions and Future Work

- Summary contributions and findings
- Limitations
  - Job postings is a secondary data source
  - Does not use external resource
  - Student skills database contained more diverse content than desired
  - Syllabi content is a proxy to course competencies
- Next steps

Conclusions and Future Work

- Summary contributions and findings
- Limitations
- Next steps
  - Extend labeled dataset and retrain classifier
  - Explore other text classification models
  - Additional within-sector analyses