Overlearning speaker gender in sociolinguistic auto-coding: Metrics and remedies

Dan Villarreal

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Overview

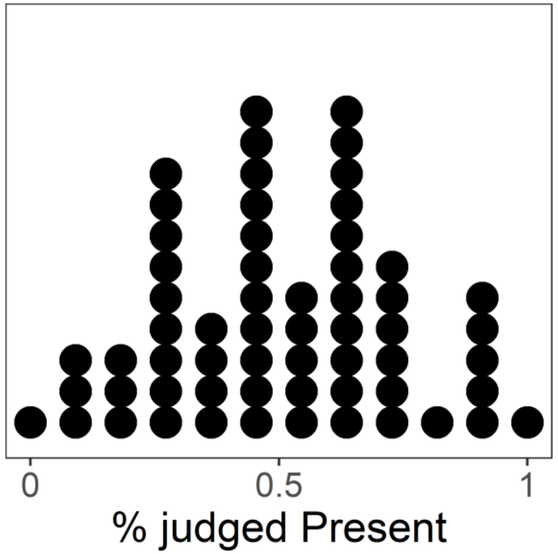
- Today I'll discuss **sociolinguistic auto-coding (SLAC)**, a computational method for classifying variable linguistic data based on acoustic features (Kendall et al. 2021; McLarty et al. 2019; Villarreal et al. 2020)
- I consider SLAC through the lens of **AI fairness** in three steps:
  1. Defining fairness in the context of SLAC
  2. Assessing fairness in a SLAC use case

     Spoiler alert: SLAC is unfair!
  3. Mitigating unfairness via several strategies

     Spoiler alert: SLAC unfairness can be mitigated—but at the cost of auto-coding accuracy

Sociolinguistic auto-coding in a nutshell

- If we want to do a variationist analysis of a categorical variable, we first need to code the variable: label tokens with variants
- But coding is hard
  - Time-consuming, tedious labor
  - /r/ notoriously hard to code, with inter-coder reliability % in the low 80s (Fosler-Lussier et al. 2007; Lawson et al. 2014; Pitt et al. 2005; Yaeger-Dror et al. 2009)
    - Right: 11 phonetically trained listeners judged 60 /r/ stimuli as Present/Absent. Most stimuli received little agreement (Villarreal et al. 2020)
- The solution? Make computers do the work!
  - Like other pinch-points in the sociolinguistic research workflow: phonetic alignment (e.g., McAuliffe et al. 2017), vowel measurement (e.g., Barreda 2021), transcription (e.g., Wassink et al. 2018)



Sociolinguistic auto-coding in a nutshell

- Enter **sociolinguistic auto-coding (SLAC)**!
- Villarreal et al. (2020): https://is.gd/djv012
  - 4,689 hand-coded /r/ tokens, 72.2% Absent (more on the speech community soon)
  - 180 acoustic measures (many speaker-normalized): formants (at numerous timepoints), pitch, amplitude, timing
  - Implemented using random forests in R w/ packages `caret` & `ranger`
  - Performance assessed using cross-validation (training data ≠ test data)
- Auto-coder performed well enough:
  - Accuracy: 84.5% (compares favorably to human inter-coder reliability)
    - That is, the auto-coder identified the correct variant for 84.5% of tokens
  - 'True positive' rate for minority Present class (62.2%) poor compared to majority Absent class (93.1%)
    - That is, the auto-coder identified only 62% of Present tokens as Present!

But…is it **fair**?

…and if it wasn’t, **how would we know**?

AI fairness

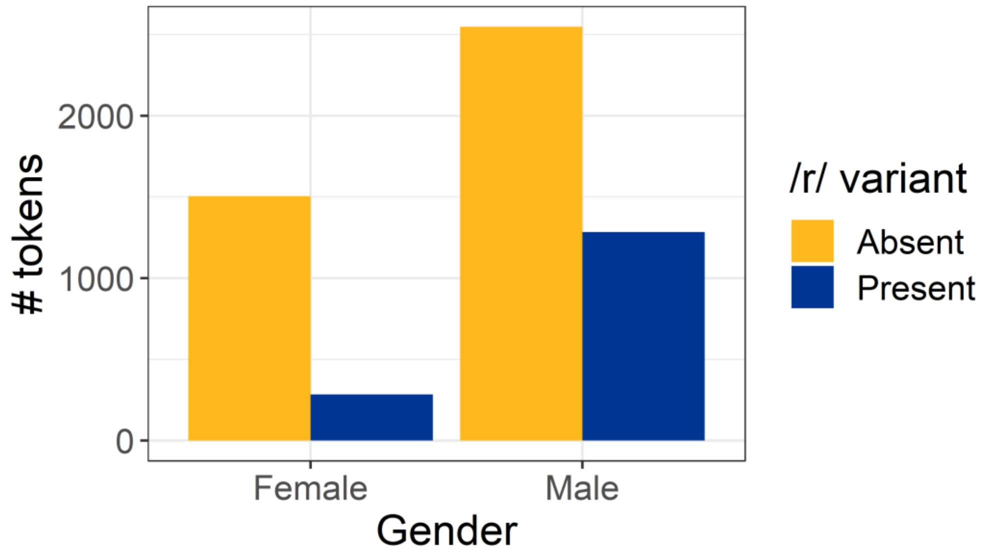
- Angwin et al. (2016) raised concerns that COMPAS, a proprietary algorithm assessing the risk of a pretrial defendant, inadvertently uses defendants' race as a decision criterion
  - Race is *not* an explicit part of the training data for COMPAS
  - Yet COMPAS **overlearns** race by implicitly recovering racial identification from questions such as those about parents' criminal record and peers' drug use
  - As a result, lower-risk Black defendants are erroneously classified as higher-risk
- In theory, SLAC could also be prone to predictive bias, if it makes predictions based *not* on legitimate cues to class membership, but instead inadvertently on group membership

Fairness metrics

- Theoretical research on AI fairness has found that there are multiple **fairness metrics**—and they're (almost always) mutually incompatible (e.g., Berk et al. 2018; Corbett-Davies et al. 2017; Kleinberg et al. 2017)
  - Mutually compatible *only* when base rates are identical (Berk et al. 2018)
- As a result, there is no single ideal fairness metric for all AI applications
- I argue an optimally fair /r/ auto-coder should minimize these three:
  - **Overall accuracy difference**: How much better/worse does the auto-coder work for *all* tokens (regardless of variant) from women vs. men?
  - **Absent class accuracy difference**: How much better/worse does the auto-coder work for *Absent* tokens from women vs. men?
  - **Present class accuracy difference**: the same, but for *Present* tokens
- Other metrics like statistical parity (equal % of predicted Absent/Present for women vs. men) don't make sense for SLAC

Fairness in Villarreal et al. (2020) auto-coder

- Data from Southland New Zealand English, NZ's only regional accent
  - Variably rhotic, unlike non-rhotic General NZE
- In the NZ popular imagination, rhoticity is linked with rugged, rural masculinity considered iconic of Southland (Villarreal et al. 2021)
- Indeed, in the training set, men are significantly more rhotic than women
  - Men's tokens also outnumber women's 2-to-1
- If unfairness is simply a matter of representation in the data, then men should be coded better than women
- Assessed fairness by breaking down performance by speaker gender



Fairness in Villarreal et al. (2020) auto-coder

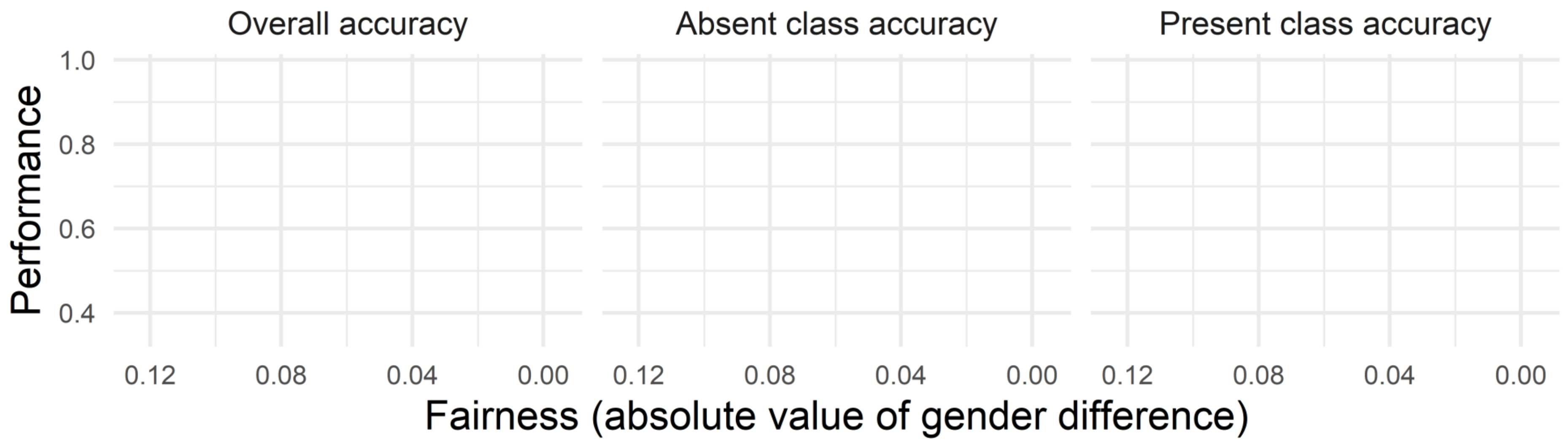
- All 3 metrics: **unfair** 😱
  - Statistically significant differences
- For overall accuracy, women > men
  - Size of training set doesn't guarantee good auto-coding performance
- Women coded better for Absent, men coded better for Present
  - Mirrors the training set's overall /r/ ~ gender pattern
- As a result, this classifier's failure to satisfy SLAC fairness criteria is likely due to **overlearning** some features that correlate with gender

	Female	Male	F − M
OvAcc	89.1%	82.2%	+6.9pp

Unfairness mitigation: Methods

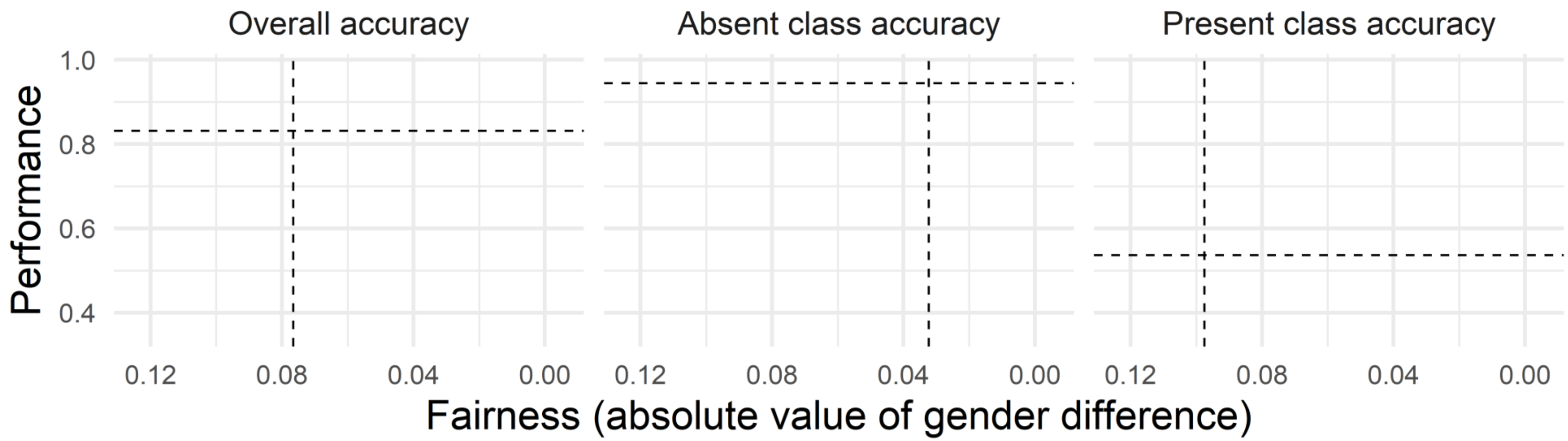
- Various **unfairness mitigation strategies** (UMSs) have been suggested, many of which amount to “systematically hide information from the model that might be contributing to unfairness”
- I tested 4 types of UMS, with 17 different implementations:
  - **Downsampling** (7 implementations): Randomly select observations to remove, to correct for imbalances in training data
  - **Valid predictor selection: empirical** (5 implementations): Remove acoustic measures empirically associated with gender
  - **Valid predictor selection: theoretical** (1 implementation): Remove acoustic measures known to be associated with gender (i.e., pitch)
  - **Combinations of above strategies** (4 implementations)

Unfairness mitigation: Results



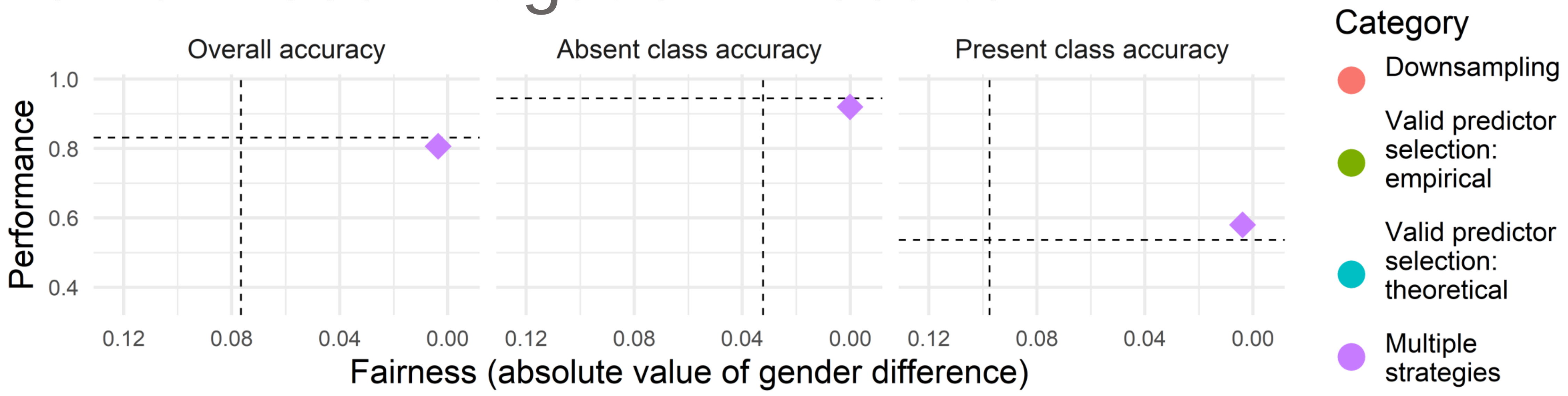
- For each sub-plot, top right = best performance **and** most fair

Unfairness mitigation: Results



- For each sub-plot, top right = best performance **and** most fair
- Dotted line = baseline classifier from Villarreal et al. (2020)

Unfairness mitigation: Results



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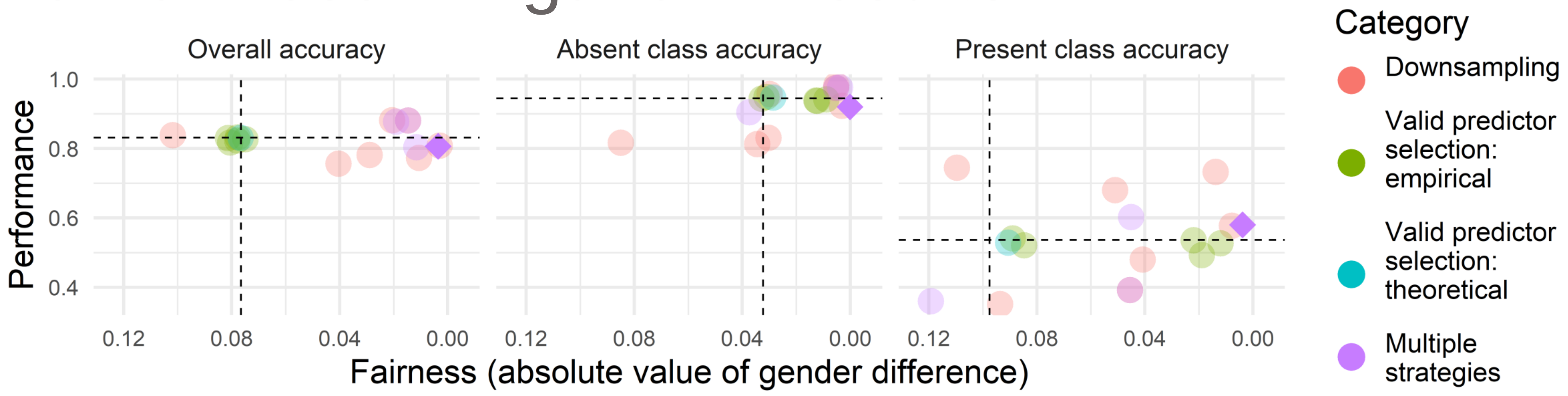
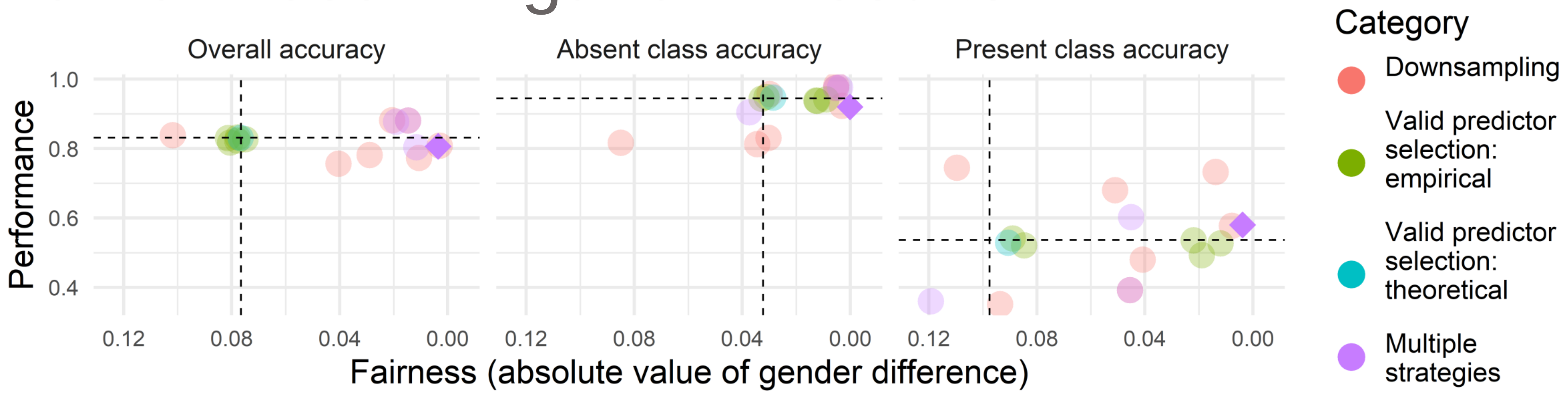
- Diamond = UMS with maximal fairness

Unfairness mitigation: Results



- For each sub-plot, top right = best performance **and** most fair
- Dotted line = baseline classifier from Villarreal et al. (2020)
- Diamond = UMS with maximal fairness
- Dots = Sub-optimal UMSs
- So what does all this mean?

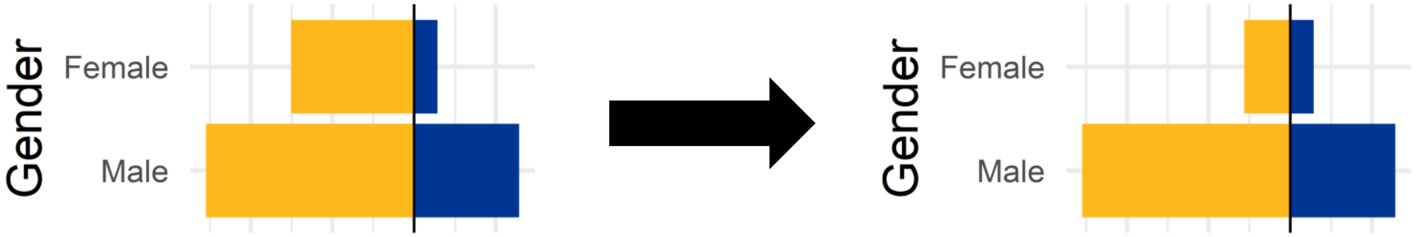
Unfairness mitigation: Results



- Numerous strategies improved fairness
  - 10 of 17 UMSs yielded no significant differences in overall accuracy
- Some strategies failed to improve fairness, or even exacerbated bias
- Many (but not all) strategies that improved fairness worsened performance
  - This includes the UMS with maximal fairness

Unfairness mitigation: Results

- Optimal UMS combined **downsampling** (decreasing female Absent to yield equal /r/ base rates by gender) **+ removing 4 pitch features**



- Unfairness shrank to near-zero
- This came at the expense of classes where women/men had previously been over-represented
  - For example, men's Present accuracy dropped 6.3pp from 64.4%

	Female	Male	F − M
OvAcc	80.4%	80.7%	**-0.4pp**
ClassAcc Absent	92.0%	92.0%	**+0.001pp**
ClassAcc Present	57.1%	58.1%	**-0.4pp**

Sociolinguistic auto-coding and AI fairness

- Like other AI applications, SLAC is indeed prone to predictive bias
  - In this case, gender unfairness is caused by overlearning an association between speaker gender and acoustic features in the feature set, and
- SLAC represents a unique use case for understanding AI fairness
  - Statistical parity—arguably the most important fairness criterion in use cases like pretrial risk detection—is wholly inappropriate for SLAC
- Mitigating cross-group unfairness in SLAC is possible, albeit at the expense of overall performance (accuracy)
  - When we used auto-coded data to compare gender differences in rhoticity in Southland, we decided the performance loss was worth it (Villarreal et al. 2021)
- **Algorithms are never, *never* neutral**. They're the result of choices by human designers—so they reflect our priorities, biases, and mistakes

Thanks! Questions?

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Dan Villarreal
d.vill@pitt.edu
github.com/djvill