Efficient Randomized Experiments Using Foundation Models

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joint work with

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- Randomized experiments are costly and time-consuming
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  - Examples: language models trained on large text corpuses, clinical models trained on observational data
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  - **But...** inferences may not be valid if model predictions are inaccurate
- **Our goal**: Reduce required sample size of randomized trials with externally trained models while guaranteeing valid statistical inference

Problem setting

- **Distribution:** $\mathbb{P}$ over $(X, Y(0), Y(1), Y, A)$
  - $X \in \mathbb{R}^d$ are covariates
  - $Y \in \mathbb{R}$ is the observed outcome (bounded)
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- **Task:** Efficiently estimate $\theta := \mathbb{E}[Y(1) - Y(0)]$

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Under these assumptions:

$$\theta = \mathbb{E}[Y(1) - Y(0)] = \mathbb{E}[Y|A = 1] - \mathbb{E}[Y|A = 0]$$

Difference in means estimator

- The simplest approach for randomized experiments:

$$\widehat{\theta}_{\mathrm{DM}} = \frac{1}{n_1} \sum_{i:A_i=1} Y_i - \frac{1}{n_0} \sum_{i:A_i=0} Y_i, \quad \text{where} \quad n_a = |\{i : A_i = a\}|$$

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- **Is this the most efficient estimator?** No, covariates are ignored!

Leverage **availability of covariates** $\rightarrow$ smaller confidence intervals

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- Introduced as Augmented Inverse Propensity Weighted (AIPW) estimator by Robins et al. '94 where $\hat{h}$ is trained on RCT
- Similar to PPI-style estimators as in Angelopoulos et al. '23 where $\hat{h}$ can be any external model

Standard AIPW using in-trial data

- In practice, standard AIPW uses a simple outcome model $\hat{h}$ (e.g. linear) learned on **RCT data**

$$\hat{h}(\cdot, a) \in \arg\min_{h \in \mathcal{H}} \frac{1}{n_a} \sum_{i:A_i = a} \mathcal{L}(Y_i, h(X_i, a))$$

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  - and if $\hat{h}$ asymptotically converges to $h^\dagger$, we have

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- Variance $V_{h^\dagger}$ is minimized when $h^\dagger = \mathbb{E}[Y|X, A]$, achieving the lowest possible variance among all regular estimators

AIPW limitations and new opportunities

- In RCTs, sample size is too small.
  - Unlikely to learn a good outcome regression from $(X_i, Y_i, A_i)_{i=1}^n$.
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- **Opportunity:** Leverage external data to learn better outcome models
  - For medical applications:
    - Electronic Health Records (EHR)
    - Large observational studies
    - Historical clinical trials
  - For social sciences (results in this paper):
    - Foundation models trained on publicly available texts

Leveraging external data

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  - Naively using external models could yield *worse* efficiency than standard AIPW
- What guarantees can we still have if we use an external model without requiring any additional assumptions?
  - Need to fall back to trial data when external models perform poorly

Related Work

Method	**Unbiased**	**Can be asympt. better than standard AIPW**	**Asympt. no worse than standard AIPW**
Standard AIPW	✓	N/A	N/A

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H-AIPW **(Ours)**	✓	✓	✓

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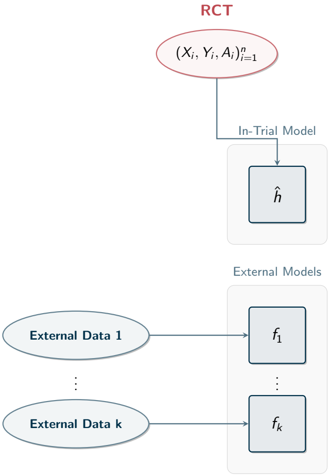

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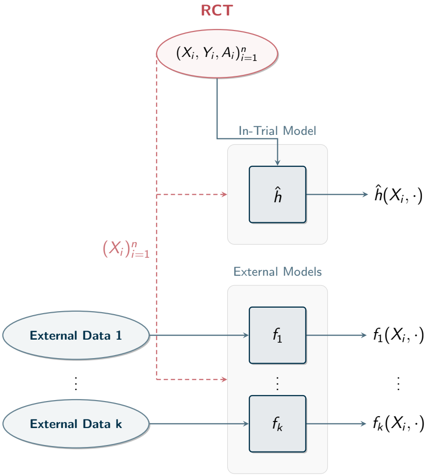

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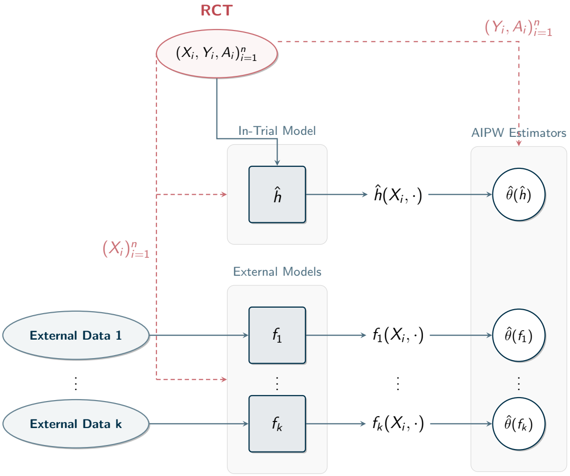

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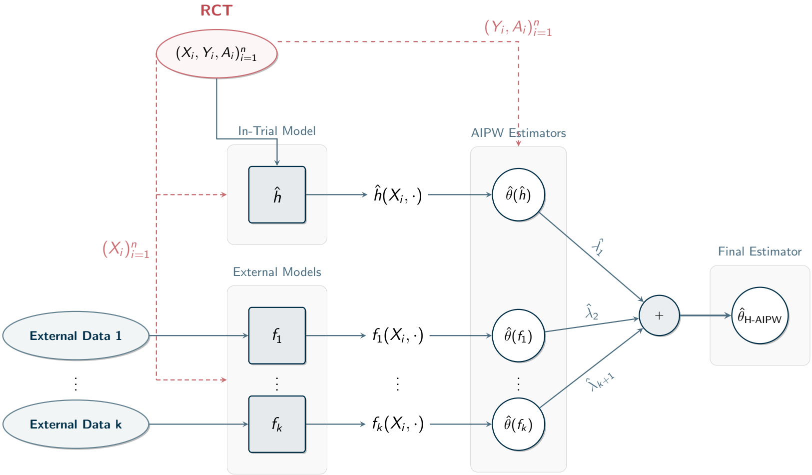

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H-AIPW Estimator

$$\widehat{\theta}_{\lambda} = \lambda_1 \widehat{\theta}_{\text{AIPW}}(\hat{h}) + \sum_{j=1}^{k} \lambda_{j+1} \widehat{\theta}_{\text{AIPW}}(f_j)$$

where $\lambda \in \mathbb{R}^{k+1}$ such that $\sum_{j=1}^{k+1} \lambda_j = 1$

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- H-AIPW inherits all the nice theoretical properties of AIPW

How to choose λ?

- True optimal weights minimize the variance of the combined estimator

$$\lambda^* = \arg\min_{\lambda} \lambda^T \Sigma \lambda \quad \text{subject to} \quad \sum_{j=1}^{k+1} \lambda_j = 1$$

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- $\Sigma \in \mathbb{R}^{(k+1)\times(k+1)}$ is the covariance matrix with elements:

$$\Sigma_{jl} = \text{Cov}(\psi(Z, g_j), \psi(Z, g_l))$$

where $\psi(Z, g)$ is the influence function corresponding to $\hat{\theta}_{AIPW}(g)$
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- Closed-form solution:

$$\lambda^* = \frac{\Sigma^{-1}\mathbf{1}}{\mathbf{1}^T\Sigma^{-1}\mathbf{1}} \quad \text{and in practice:} \quad \widehat{\lambda} = \frac{\widehat{\Sigma}^{-1}\mathbf{1}}{\mathbf{1}^T\widehat{\Sigma}^{-1}\mathbf{1}}$$

Statistical Guarantees

With this choice of weights λ, we obtain the asymptotic guarantees:

Theorem (H-AIPW Guarantees) in DAWDDYD '25:

(a) **Consistency and Asymptotic Normality:**

$$\sqrt{n}(\widehat{\theta}_{\hat{\lambda}} - \theta) \rightsquigarrow \mathcal{N}(0, V_{\lambda^*})$$

(b) **Efficiency Guarantee:** The asymptotic variance is no greater than any individual estimator:

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- If models are accurate, may have smaller asymptotic variance!

Empirical evaluation on real data

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  - Foreign Policy (Silverman, 2022)
  - Sociology (Melin, 2022; Kennedy, 2020; Caprariello, 2013)
  - Political Science (Fahey, 2023)
  - Psychology (Brandt, 2021)
  - Economics (Haaland, 2022)

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  - Political Science (Fahey, 2023)
  - Psychology (Brandt, 2021)
  - Economics (Haaland, 2022)
- Foundation models used:
  - GPT-4o, Claude 3.5 Haiku, LLaMA 3 70B
  - Multiple prompts (10 per model) to improve accuracy
- We compare against:
  - Difference in means estimator
  - Standard AIPW with (linear) outcome regression from trial data
  - PPI based PPCT (Poulet, 2025) also leveraging foundation models

Concrete Example: LLM Predictions for Political Science

- **A=0**: "protests banned due to safety concerns",
- **A=1**: "Protests banned safety concerns & cancel culture"
- **Outcome**: Degree of agreement with "Cancel culture is a problem"

LLM Prompt (with A=1):

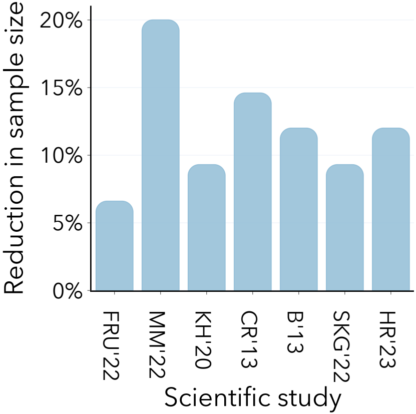
```
You are a 35-year-old female Democrat with liberal views and $75k
income. A university banned an Antifa protest citing safety concerns
and that such protests contribute to cancel culture.
How much do you agree: "Cancel culture is a big problem in today's
society"? (1-5 scale)
```

LLM Response:

As someone with liberal views, I'm skeptical of the university's framing. While I believe in maintaining safety, linking Antifa protests to "cancel culture" seems politically motivated.
I'd rate my agreement as **2** - **Disagree**.

Sample size reductions

- Each study is subsampled to $n = 75$ participants



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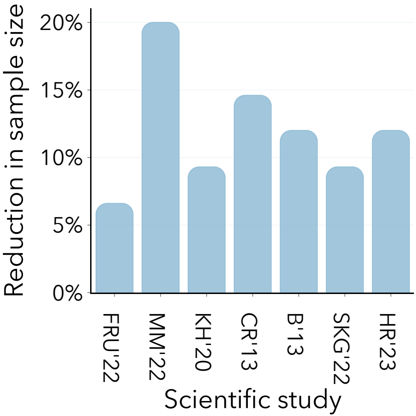
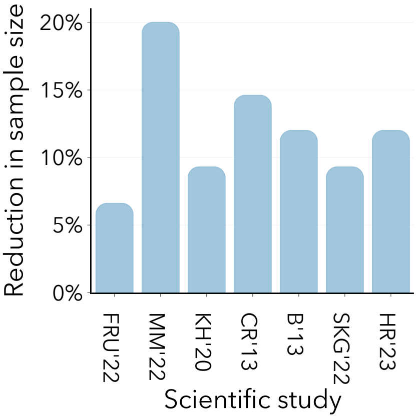


Sample size reductions

- Each study is subsampled to $n = 75$ participants
- The bars show the percentage sample size reduction to match confidence interval width of standard AIPW
- H-AIPW achieves the same precision as standard AIPW with up to 20% fewer samples

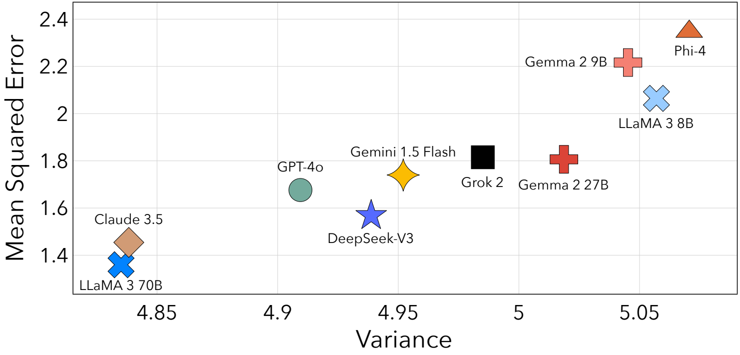


Variance reduction

Estimator	Melin et al. (2022) $n=100$	Melin et al. (2022) $n=200$	Silverman et al. (2022) $n=100$	Silverman et al. (2022) $n=200$	Kennedy et al. (2020) $n=100$	Kennedy et al. (2020) $n=200$	Fahey et al. (2023) $n=100$	Fahey et al. (2023) $n=200$
H-AIPW	**10.39**	**10.28**	**2.10**	**2.14**	**17.09**	**17.47**	**4.87**	4.94
PPCT	11.00	11.06	2.25	2.26	17.87	17.97	4.88	**4.91**
PROCOVA	11.81	10.62	2.24	2.22	18.38	18.11	5.18	5.09
AIPW (boosting)	12.82	12.44	2.82	2.83	23.09	23.12	6.31	6.37
AIPW (standard)	11.72	10.57	2.22	2.20	18.09	17.95	5.09	5.04
DM	11.10	11.10	2.30	2.30	18.07	18.08	5.61	5.62

Estimator	Caprariello et al. (2013) $n=100$	Caprariello et al. (2013) $n=200$	Brandt (2013) $n=100$	Brandt (2013) $n=200$	Haaland et al. (2023) $n=100$	Haaland et al. (2023) $n=200$	Shuman et al. (2024) $n=100$	Shuman et al. (2024) $n=200$
H-AIPW	**5.88**	**5.96**	**11.86**	**11.90**	**4.49**	**4.44**	**8.46**	**8.91**
PPCT	5.99	6.01	12.07	12.12	4.50	4.52	9.08	9.14
PROCOVA	6.41	6.13	12.77	12.25	4.73	**4.44**	9.12	9.55
AIPW (boosting)	7.79	7.60	15.20	14.70	5.39	5.22	10.53	10.67
AIPW (standard)	6.39	6.18	12.55	12.13	4.82	4.55	9.20	10.31
DM	6.15	6.15	12.81	12.80	5.72	5.71	13.83	13.83

Impact of model scale



Larger models tend to provide better predictions, leading to smaller variance and better efficiency gains

Conclusion

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GitHub repository: `https://github.com/jaabmar/HAIPW`

Thank You! Any Questions?

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