Latent Civil War

Improving Inference and Forecasting with a Civil War Measurement Model

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Motivations

We start with both substantive and methodological motivations:

- Can we characterize the measurement uncertainty in civil war status?
- What implications does this have for studies of civil war onset?

- Improving dynamic latent variable models
- Handling measurement uncertainty in dependent variables
- Posterior bagging: an improved forecasting technique for low-data settings

Table of Contents

1. Latent Civil War
2. Validating the Model
3. Incorporating Uncertainty
4. Forecasting with Posterior Bagging

Civil War as a Latent Variable

Like many variables in political science (e.g., democracy, respect for human rights, ideology...) civil war is latent.

- Can't be observed directly
- Single, underlying trait
- Multiple, potentially noisy and biased observations

Civil War Datasets

We use eight separate codings of civil war.

We assume that each of these measure the same underlying trait, but with different thresholds (usually battle deaths/year).

- PITF Major Episodes of Political Conflict
- Correlates of War
- Fearon and Laitin (2003)
- Collier and Hoeffler (2002)
- Doyle and Sambanis (2000)
- UCDP major armed conflict
- UCDP major or minor armed conflict
- ICEWS Ground Truth Dataset

country	year	icews	pitf	F&L	S&D	C&H	UCDP major	UCDP minor	cow
Afghanistan	1994	NA	1	1	1	1	1	1	1
Afghanistan	1995	NA	1	1	1	1	1	1	1
Afghanistan	1996	NA	1	1	1	1	1	1	1
Afghanistan	1997	NA	1	1	1	1	1	1	1
Afghanistan	1998	NA	1	1	1	1	1	1	1
Afghanistan	1999	NA	1	1	1	1	1	1	1
Afghanistan	2000	NA	1	NA	NA	NA	1	1	1
Afghanistan	2001	1	1	NA	NA	NA	1	1	1
Afghanistan	2002	1	1	NA	NA	NA	0	1	0
Afghanistan	2003	1	1	NA	NA	NA	0	1	0
Afghanistan	2004	1	1	NA	NA	NA	0	1	0
Afghanistan	2005	1	1	NA	NA	NA	1	1	0
Afghanistan	2006	1	1	NA	NA	NA	1	1	0
Afghanistan	2007	1	1	NA	NA	NA	1	1	0
Afghanistan	2008	1	1	NA	NA	NA	1	1	0
Afghanistan	2009	1	1	NA	NA	NA	1	1	0

Simple IRT Setup

Each country-year has a latent civil war status θ_{it}.

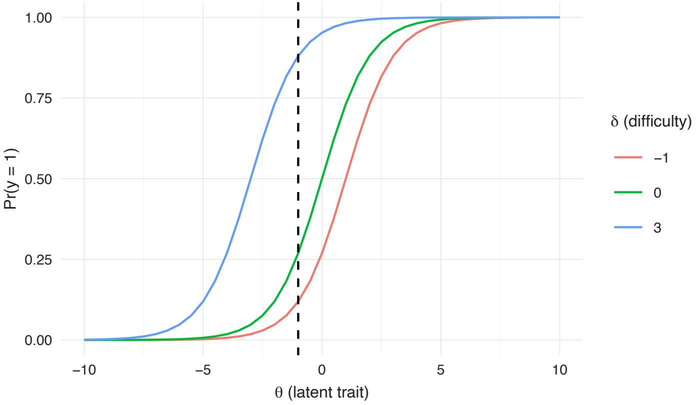
The probability that rater *k* rates country *i* in year *t* as having a civil war is given by:

$$P(y_{itk} = 1 | \theta_{it}, \alpha_k, \delta_k) = \text{logit}^{-1}(\alpha_k(\theta_{it} - \delta_k)),$$

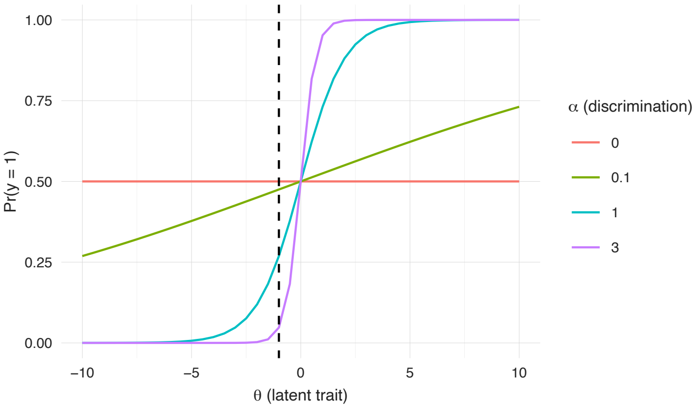
where

- θ_{it} is the latent probability of civil war for the country-year
- α_k is a per-rater “discrimination" or “reliability" parameter
- δ_k is a per-rater “bias" or “difficulty" term

Example: varying δ parameter



Example: varying α parameter



Dynamic Model of Civil War

CIvil war status is autocorrelated, but can experience large changes in status. We thus need models that allow large changes while still keeping variance low.

- “Robust" model (Reuning, Kenwick and Fariss 2019)
- Switching model

- Random effects
- Bayesian data reweighting (Wang, Kucukelbir and Blei 2017)

- Random effects + weighting
- Switching + weighting

“Robust" dynamic IRT (Reuning, Kenwick and Fariss 2019)

- How can we allow both autocorrelation and large changes in the latent status?
- Reuning, Kenwick and Fariss (2019) suggest a random walk with a Student’s *t* distribution with 4 degrees of freedom:

$$\theta_{c,t} \sim \begin{cases} \mathrm{T}_4(\theta_{c,t-1}, \sigma) & \text{if } t > 1 \\ \mathrm{T}_4(0, \sigma) & \text{if } t = 1 \end{cases}$$
$$\sigma \sim \text{Exponential}(1)$$

This outperforms a static model and a normally distributed walk.

“Switching" model

Next, we propose a theoretically motivated model that allows for explicit switches in status:

$$
\begin{aligned}
\theta_{c,t}^{\text{peace}} &\sim \begin{cases} \mathrm{T}_4(\theta_{c,t-1}^{\text{peace}}, \sigma^{\text{peace}}) & \text{if } t > 1 \\ \mathrm{T}_4(\mu^{\text{peace}}, \sigma^{\text{peace}})) & \text{if } t = 1 \end{cases} \\
\theta_{c,t}^{\text{transition}} &\sim \mathrm{T}_4(\mu^{\text{transition}}, \sigma^{\text{transition}})) \\
\theta_{c,t}^{\text{war}} &\sim \begin{cases} \mathrm{T}_4(\theta_{c,t-1}^{\text{war}}, \sigma^{\text{war}}) & \text{if } t > 1 \\ \mathrm{T}_4(\mu^{\text{war}}, \sigma^{\text{war}})) & \text{if } t = 1 \end{cases} \\
\mu^{\text{peace}}, \mu^{\text{transition}}, \mu^{\text{war}} &\sim \text{Normal}(0, 5) \text{ s.t. } \mu^{\text{peace}} < \mu^{\text{transition}} < \mu^{\text{war}} \\
\pi &\sim \text{Dirichlet}(\mathbf{0.01})
\end{aligned}
$$

The final log-likelihood is given by $\sum_{s \in \{\text{war, peace, transition}\}} \pi^{(s)} \theta_{ct}^{(s)}$

Random Effects IRT

Next, we allow the difficulty and discrimination to vary by country-year, with a hierarchical model:

$$
\begin{aligned}
\theta_{c,t} &\sim \begin{cases} T_4(\theta_{c,t-1}, \exp(\sigma_{c,t})) & \text{if } t > 1 \\ T_4(0, \exp(\sigma_{c,t})) & \text{if } t = 1 \end{cases} \\
\alpha_{k,c} &\sim \text{Normal}(\mu_{\alpha_k}, \Sigma_\alpha) \\
\delta_{k,c} &\sim \text{Normal}(\mu_{\delta_k}, \Sigma_\delta) \\
\sigma_{c,t} &\sim \text{Normal}(\mu_{\sigma_c}, 1) \\
\mu_{\alpha_k}, \mu_{\delta_k}, \mu_{\sigma_c} &\sim \text{Normal}(0, 1) \\
\Sigma_\alpha &= \text{Diag}(\tau_\alpha) \times \Omega_\alpha \times \text{Diag}(\tau_\alpha) \\
\Sigma_\delta &= \text{Diag}(\tau_\delta) \times \Omega_\delta \times \text{Diag}(\tau_\delta) \\
\tau_\alpha, \tau_\delta &\sim \text{Cauchy}(0, 2.5) \\
\Omega_\alpha, \Omega_\delta &\sim \text{LKJCorr}(2)
\end{aligned}
$$

Bayesian data reweighting

Another source of variance in the posterior could come from corrupted data. (Intuition: an idiosyncratic rater-country-year error term).

Possible solution: Bayesian data reweighting (Wang, Kucukelbir and Blei 2017):

$$p(\boldsymbol{\Theta}, \mathbf{w}|y) \propto p_{\boldsymbol{\Theta}}(\boldsymbol{\Theta}) p_{\mathbf{w}}(\mathbf{w}) \prod_{i=1}^{N} \ell(y_i|\boldsymbol{\Theta})^{w_i}$$

$$\mathbf{w} \sim \text{Dirichlet}(\mathbf{1})$$

where **w** is a vector of positive latent weights.

Table of Contents

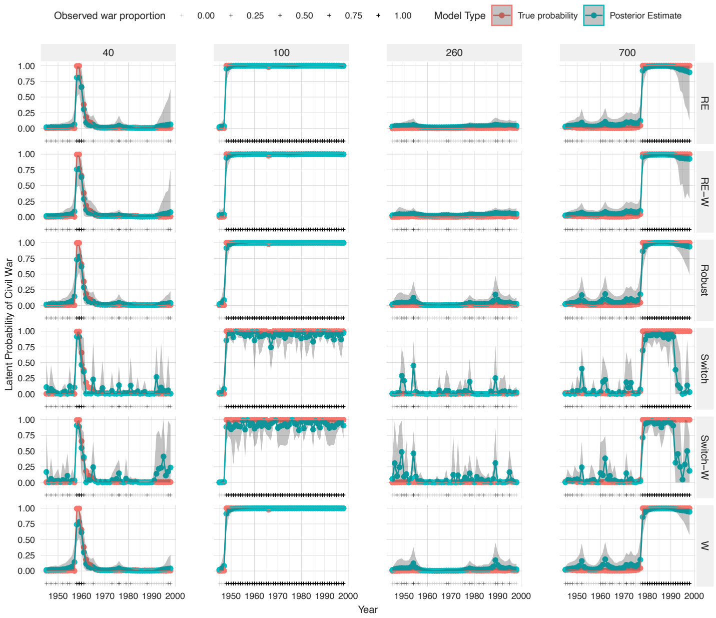
1. Latent Civil War
2. Validating the Model
3. Incorporating Uncertainty
4. Forecasting with Posterior Bagging

Accuracy on semi-simulated data

First, we evaluate performance on simulated data.

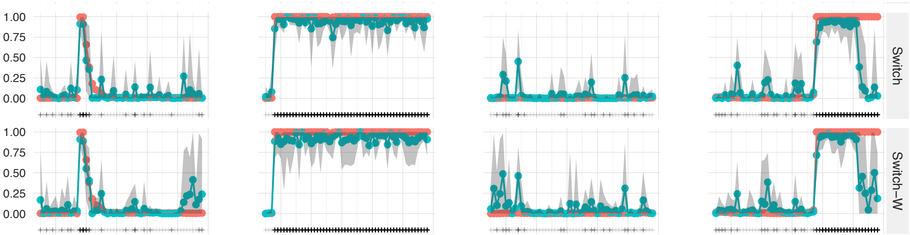
Generating simulated data is difficult–we opt for a semi-simulated approach that generates a latent war probability from an existing (binary) war dataset. (Details in appendix)

	Model	RE	W	Switch	RMSE	Acc.	F1	α correct	δ correct
1	RE	✓			0.07	0.99	0.97	1.00	0.50
2	RE-W	✓	✓		0.07	0.99	0.97	1.00	0.25
3	Simple "Robust"				0.08	0.99	0.98	1.00	1.00
4	W		✓		0.08	0.99	0.98	1.00	1.00
5	Switching			✓	0.11	0.99	0.96	1.00	0.50
6	Switching-W		✓	✓	0.11	0.99	0.96	1.00	0.50

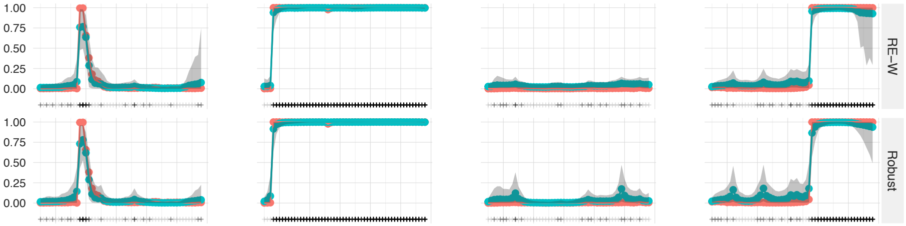

Observed war proportion
0.00
0.25
0.50
0.75
1.00
Model Type
True probability
Posterior Estimate
40
100
260
700
RE
RE−W
Robust
Switch
Switch−W
W
Latent Probability of Civil War
Year
1950 1960 1970 1980 1990 2000

Switching Models

The switching models suffer from “phantom" onsets and high variance:

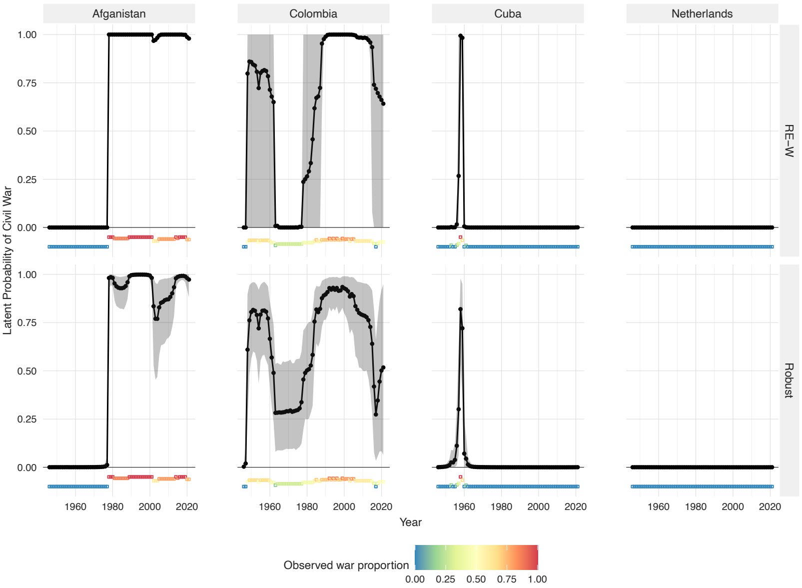


The “robust" models and the random effects + reweighting models do much better:



The RE+W model has a slight qualitative improvement in “jumping" behavior over the robust model.

Comparison to actual data



Difficulty Parameters

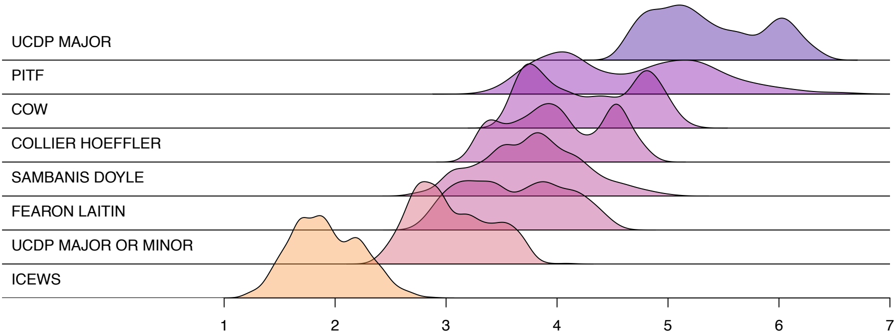


Table of Contents

1. Latent Civil War
2. Validating the Model
3. Incorporating Uncertainty
4. Forecasting with Posterior Bagging

Rubin's rule

Existing studies of civil war onset consider only sampling uncertainty. But we should also account for measurement uncertainty.

We build on Schnakenberg and Fariss (2014) and Crabtree and Fariss (2015) to incorporate measurement uncertainty using Rubin's rule from multiple imputation:

$$\mathrm{SE}(\theta) = \sqrt{\frac{1}{M}\sum_{i=1}^{m}\mathrm{SE}(\theta_i)^2 + S_\theta^2(1+1/m)}$$

where the sample variance of θ across m estimates is: $S_\theta^2 = \sum_{i=1}^{m} \frac{(\theta_j - \bar{\theta})^2}{(m-1)}$.

(Thanks to Max for correcting an error here!)

Reanalyzing Fearon and Laitin (2003)

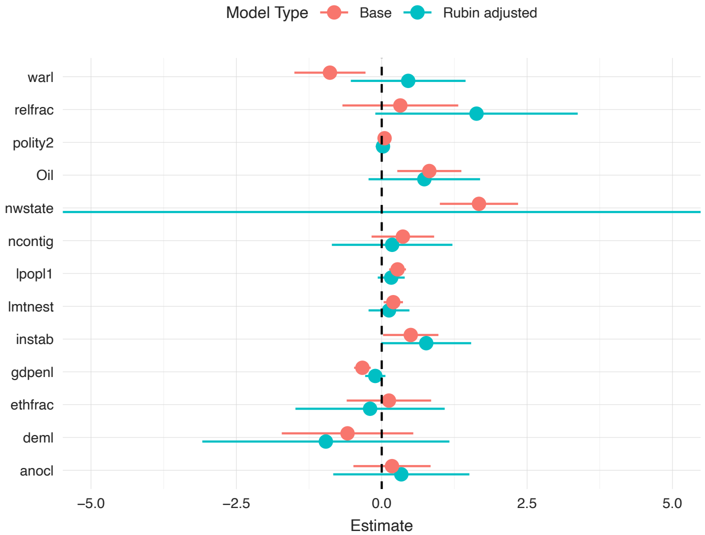


Table of Contents

1 Latent Civil War

2 Validating the Model

3 Incorporating Uncertainty

4 Forecasting with Posterior Bagging

Improving forecasts through lower variance

- Much of the focus in civil war forecasting is on reducing the bias of models by fitting more flexible models.
- Recall the bias-variance decomposition of mean squared error:

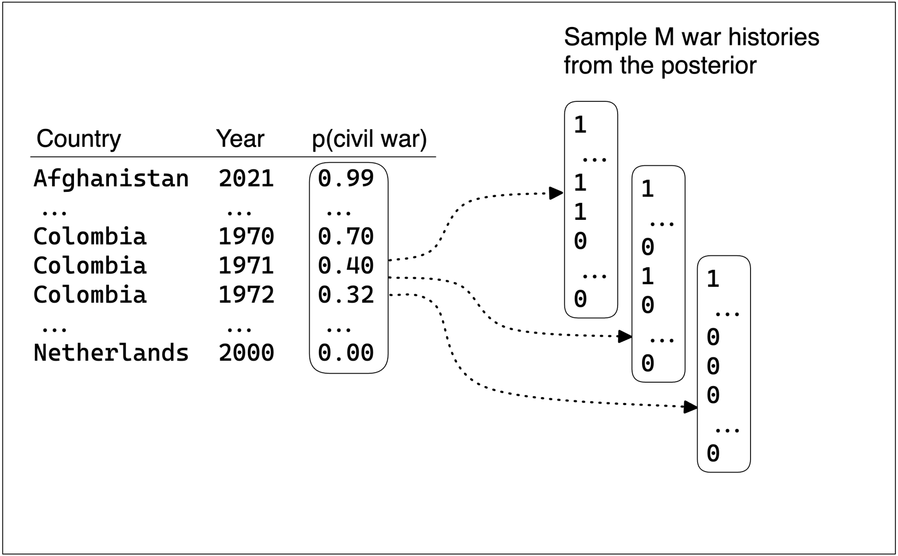
$$\text{MSE} = (y - \mathbb{E}[\hat{y}])^2 + \mathbb{V}[\hat{y}] + \sigma^2$$

- Reducing the variance of (unbiased) models will reduce the MSE.

Bagging and Posterior Bagging

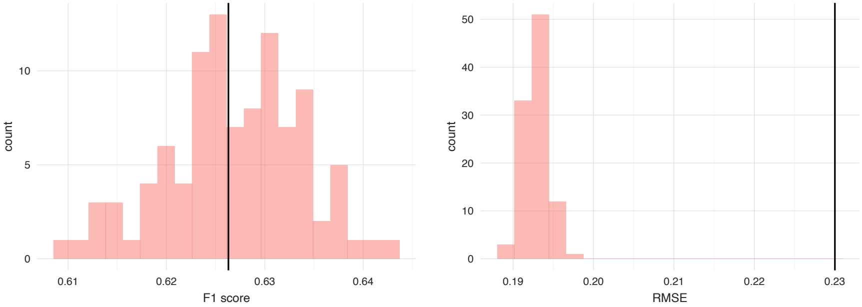
- Breiman (1996) introduces bagging, a technique for aggregating predictive models fit on bootstrap draws from the original data.
- When the variance across predictions is high, the bootstrap-aggredated predictor will outperform single predictive models. [Proof]
- Idea: We can induce variance in our predictors by sampling from the posterior estimate of civil war, rather than bootstrapping.
- Posterior bagging is a flexible approach for improvement models when the dependent variable is measured with error.

Posterior bagging



Forecasting Results–full time period

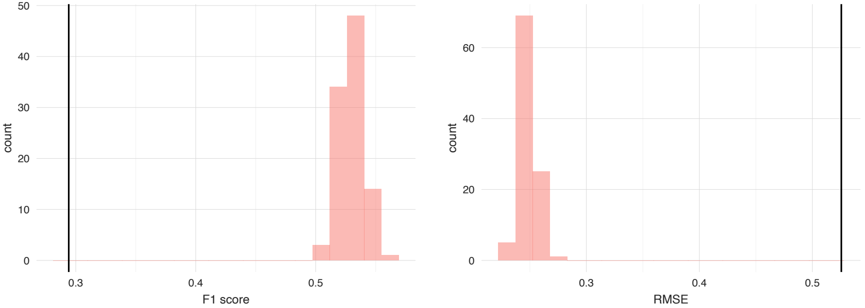
Evaluating forecast on out-of-sample onsets.
F1 and RMSE, vertical line shows results from single logistic regression model.



Trained on the full period, posterior bagging provides no improvement in F1 score, but provides better calibrated forecasts.

Restricted sample forecasting

However, when using 10 years of training data, posterior bagging greatly outperforms a single model:



F1 (left) and RMSE (right), comparing forecasts trained on 10 years of data with out-of-sample onsets. Vertical line shows results from single logistic regression model.

Conclusions

- Civil war is clearly measured with error–a new dynamic measurement model quantifies the uncertainty in civil war status.
- Posterior bagging offers a flexible approach to improvement forecasting models.

Future work:

- Extending single datasets forward and backward in time
- Correlation between errors and covariates
- Improved dynamic models

Thank you!

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Backup Slides

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Semi-simulated data

We generate semi-simulated data with latent war status from Fearon and Laitin's (2003) observed civil war status (Y_{it}):

$$
\begin{aligned}
Y^*_{it} = 0.8 \cdot Y^*_{i,t-1} & \quad \text{autocorrelation in status} \\
+ (1 - Y_{it})\mathcal{N}(-1, 0.3) & \quad \text{downward trend during peace} \\
+ Y_{it}\mathcal{N}(0.6, 1) & \quad \text{upward trend during war} \\
+ S_{it}\mathcal{N}(5, 1) & \quad \text{positive shock for onset} \\
+ (1 - S_{it})\mathcal{N}(-4, 1) & \quad \text{negative shock for termination} \\
+ S_{i,t+1}\mathcal{N}(1, 1) & \quad \text{increase in the year before onset} \\
+ S_{i,t+1}\mathcal{N}(1, 1) & \quad \text{increase in the year following termination}
\end{aligned}
$$

Bagging derivation (Breiman 1996)

$\mathcal{L}$: set of bootstrap draws $\{(x, y), (x, y)...\}$ from original data X.
$\phi(X, \mathcal{L})$: predictor for y given $\mathcal{L}$
Define the aggregate predictor $\phi_A(X) = \mathbb{E}_{\mathcal{L}}[\phi(X, \mathcal{L})]$
We then decompose the expectation over $\mathcal{L}$ of the mean squared error:

$$\mathbb{E}_{\mathcal{L}}[(y - \phi(X, \mathcal{L}))]^2 = y^2 - 2y\mathbb{E}_{\mathcal{L}}[\phi(X, \mathcal{L})] + \mathbb{E}_{\mathcal{L}}[\phi(X, \mathcal{L})]^2$$

Recall the definition of the aggregate predictor:

$$= y^2 - 2y\phi_A(X) + \phi_A(X)^2$$

$$= (y - \phi_A(X))^2$$

by Jensen's inequality ($\mathbb{E}[Z^2] \geq \mathbb{E}[Z]^2$) :

$$\mathbb{E}_{\mathcal{L}}[y - \phi(X, \mathcal{L})^2] \geq (y - \phi_A(X))^2$$

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