ddml: Double/debiased machine learning in Stata

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Package website: `https://statalasso.github.io/`

Latest version available here

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Introduction

A rich and growing literature exploits machine learning to facilitate causal inference.

A central focus: *high-dimensional* controls and/or instruments, which can arise if

- we observe many controls/instruments
- controls/instruments enter through an unknown function

Belloni, Chernozhukov, and Hansen (2014) and Belloni et al. (2012) propose estimators *relying on the Lasso* that allow for high-dimensional controls/instruments.

⇒ Available via `pdslasso` in Stata (Ahrens, Hansen, and Schaffer, 2020)

Introduction

What if we don't want to use the lasso?

- The Lasso might not be the *best-performing machine learner* for a particular problem.
- The Lasso relies on the *approximate sparsity assumption*, which might not be appropriate in some settings.

Chernozhukov et al. (2018) propose *Double/Debiased Machine Learning* (DDML or sometimes "Double ML") which allow to exploit machine learners other than the Lasso.

Our contribution:

- We introduce `ddml`, which implements DDML for Stata.
- We provide simulation evidence on the finite sample performance of DDML.
- Our recommendation is to use DDML in combination with Stacking.

Background

Motivating example. The partially-linear model:

$$y_i = \underbrace{\boxed{\theta d_i}}_{\text{causal part}} + \underbrace{\boxed{g(\boldsymbol{x}_i)}}_{\text{nuisance}} + \varepsilon_i.$$

How do we account for confounding factors $\boldsymbol{x}_i$? — The standard approach is to assume linearity $g(\boldsymbol{x}_i) = \boldsymbol{x}_i'\beta$ and consider alternative combinations of controls.

Problems:

- Non-linearity & unknown interaction effects
- High-dimensionality: we might have “many” controls
- We don’t know which controls to include

Background

Motivating example. The partially-linear model:

$$y_i = \underbrace{\boxed{\theta d_i}}_{\text{causal part}} + \underbrace{\boxed{g(\boldsymbol{x}_i)}}_{\text{nuisance}} + \varepsilon_i.$$

Post-double selection (Belloni, Chernozhukov, and Hansen, 2014) and *post-regularization* (Chernozhukov, Hansen, and Spindler, 2015) provide data-driven solutions for this setting.

Both "double" approaches rely on the *sparsity assumption* and use two auxiliary lasso regressions: $y_i \rightsquigarrow \boldsymbol{x}_i$ and $d_i \rightsquigarrow \boldsymbol{x}_i$.

Related approaches exist for *optimal IV* estimation (Belloni et al., 2012) and/or *IV with many controls* (Chernozhukov, Hansen, and Spindler, 2015).

Background

These methods have been implemented for Stata in `pdslasso` (Ahrens, Hansen, and Schaffer, 2020), `dsregress` (StataCorp) and R (`hdm`; Chernozhukov, Hansen, and Spindler, 2016).

Example 1:

```
. clear
. use https://statalasso.github.io/dta/AJR.dta
. pdslasso logpgp95 avexpr ///
        (lat_abst edes1975 avelf temp* humid* steplow-oilres)
```

Variables in parentheses are treated as high-dimensional controls. The lasso selects from them.

Background

These methods have been implemented for Stata in `pdslasso` (Ahrens, Hansen, and Schaffer, 2020), `dsregress` (StataCorp) and R (`hdm`; Chernozhukov, Hansen, and Spindler, 2016).

Example 2:

Select controls, but specify that `logem4` is an unpenalized instrument (using `partial(logem4)`).

```
. ivlasso logpgp95 (avexpr=logem4) ///
    (lat_abst edes1975 avelf temp* humid* steplow-oilres), ///
    partial(logem4)
```

Background

There are **advantages** of relying on lasso:

- intuitive assumption of (approximate) sparsity
- computationally relatively cheap (due to plugin lasso penalty; no cross-validation needed)
- Linearity has its advantages (e.g. extension to fixed effects; Belloni et al., 2016)

But there are also **drawbacks**:

- What if the sparsity assumption is not plausible?
- There is a wide set of machine learners at disposable—Lasso might not be the best choice.
- Lasso requires careful feature engineering to deal with non-linearity & interaction effects.

$\Longrightarrow$ **DDML** (Chernozhukov et al., 2018)

Review of DDML

The partially-linear model:

$$Y = \theta_0 D + g_0(\boldsymbol{X}) + U$$
$$D = m_0(\boldsymbol{X}) + V$$

Naive idea: We estimate conditional expectation functions (CEFs) $\ell_0(\boldsymbol{X}) = E[Y|\boldsymbol{X}]$ and $m_0(\boldsymbol{X}) = E[D|\boldsymbol{X}]$ using ML and partial out the effect of $\boldsymbol{X}$ (in the style of Robinson, 1988):

$$\hat{\theta}_{DDML} = \left(\frac{1}{n}\sum_i \hat{V}_i^2\right)^{-1} \frac{1}{n}\sum_i \hat{V}_i(Y_i - \hat{\ell}),$$

where $\hat{V} = D - \hat{m}_i$.

Review of DDML

Yet, there is a problem:

- The estimation error of the first step (CEF estimation) may spill-over to the second step (estimation of structural parameters).
- For example, the estimation error $\ell(\boldsymbol{x}_i) - \hat{\ell}$ and v_i may be correlated due to *over-fitting*, leading to poor finite sample performance (*own-observation bias*).

DDML relies on two ingredients:

1. **cross-fitting:** sample splitting with swapped samples
2. **Neyman-orthogonal scores:** score functions which are robust to small perturbations

Review of DDML

Cross-fitting for the partially-linear model (DML 2)

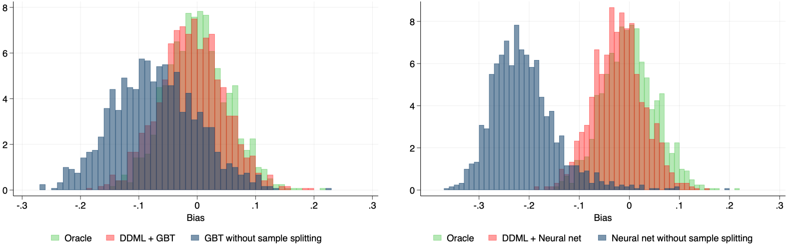
Split the sample $\{(Y_i, D_i, \boldsymbol{X}_i)\}_{i=1}^n$ randomly in K folds of approximately equal size. Denote I_k the set of observations included in fold k and I_k^c its complement.

1. For each $k \in \{1, \dots, K\}$:
   1.1 Fit a CEF estimator to the sub-sample I_k^c using Y_i as the outcome and $\boldsymbol{X}_i$ as predictors. Obtain the out-of-sample predicted values $\hat{\ell}_{I_k^c}(\boldsymbol{X}_i)$ for $i \in I_k$.
   1.2 Fit a CEF estimator to the sub-sample I_k^c using D_i as the outcome and $\boldsymbol{X}_i$ as predictors. Obtain the out-of-sample predicted values $\hat{m}_{I_k^c}(\boldsymbol{X}_i)$ for $i \in I_k$.
2. Compute

$$\hat{\theta}_n = \frac{\frac{1}{n}\sum_{i=1}^n \left(Y_i - \hat{\ell}_{I_{k_i}^c}(\boldsymbol{X}_i)\right)\left(D_i - \hat{m}_{I_{k_i}^c}(\boldsymbol{X}_i)\right)}{\frac{1}{n}\sum_{i=i}^n \left(D_i - \hat{m}_{I_{k_i}^c}(\boldsymbol{X}_i)\right)^2}. \tag{1}$$

The importance of cross-fitting: An MC illustration

DDML+learner (orange) does almost as well as the oracle (green).
Learner with no cross-fitting (blue) is biased.
(Learner (a) is gradient-boosted trees; Learner (b) is neural net.)



(a) $n = 1000$ (b) $n = 1000$

Notes: Figures (a) and (b) compare the bias of the oracle estimator (which knows the true data-generating process) and gradient-boosted trees with and without sample splitting. We generate 1'000 samples of size $n = 1000$ using the partially-linear model $Y_i = \theta_0 D_i + g(\boldsymbol{X}_i) + \varepsilon_i$, $D_i = g(\boldsymbol{X}_i) + u_i$ where the nuisance function is $g(\boldsymbol{X}_i) = \mathbb{1}\{X_{i1} > 0.3\}\mathbb{1}\{X_{i2} > 0\}\mathbb{1}\{X_{i3} > -1\}$. Gradient boosting uses 1200 trees, a maximum tree depth of 6, a learning rate of 0.1, and early stopping with 20% validation sample.

Remarks

Remark 1: Number of folds.

- The number of cross-fitting folds K is a necessary tuning choice. Theoretically, any finite value is admissable.
- Based on our simulation experience, we find that more folds tends to lead to better performance, especially when the sample size is small.

Remarks

Remark 2: Cross-fitting repetitions.

We recommend running the cross-fitting procedure more than once using different random folds to assess randomness introduced via the sample splitting.

Let $\hat{\theta}_n^{(r)}$ denote the DDML estimate from the rth cross-fit repetition and $\hat{s}_n^{(r)}$ its associated standard error estimate with $r = 1, \ldots, R$:

$$\breve{\hat{\theta}}_n = \operatorname{median}\left(\left(\hat{\theta}_n^{(r)}\right)_{r=1}^{R}\right)$$

$$\breve{\hat{s}}_n = \sqrt{\operatorname{median}\left(\left((\hat{s}_n^{(r)})^2 + (\hat{\theta}_n^{(r)} - \breve{\hat{\theta}}_n)^2\right)_{r=1}^{R}\right)}.$$

`ddml` facilitates this using the `rep(`*integer*`)` options.

DDML models

The DDML framework can be applied to other models (all implemented in `ddml`):

Interactive model

$$Y = g_0(D, \boldsymbol{X}) + U \tag{2}$$

where D is a scalar binary variable and that D is not required to be additively separable from the controls $\boldsymbol{X}$. In this setting, the parameters of interest are

$$\begin{aligned} \theta_0^{\text{ATE}} &\equiv E[g_0(1, \boldsymbol{X}) - g_0(0, \boldsymbol{X})] \\ \theta_0^{\text{ATET}} &\equiv E[g_0(1, \boldsymbol{X}) - g_0(0, \boldsymbol{X}) | D = 1], \end{aligned} \tag{3}$$

which correspond to the *average treatment effect* (ATE) and *average treatment effect on the treated* (ATET), respectively.

DDML models

The DDML framework can be applied to other models (all implemented in `ddml`):

Partially-linear IV model

$$Y = \theta_0 D + g_0(\boldsymbol{X}) + U,$$

where we leverage instrumental variables $\boldsymbol{Z}$ for identification.

Let $\ell_0(\boldsymbol{X}) \equiv E[Y|\boldsymbol{X}]$, $m_0(\boldsymbol{X}) \equiv E[D|\boldsymbol{X}]$, and $r_0(\boldsymbol{X}) \equiv E[Z|\boldsymbol{X}]$.

We assume $E[Cov(U, Z|\boldsymbol{X})] = 0$ and $E[Cov(D, Z|\boldsymbol{X})] \neq 0$, and consider the score function

$$\psi(\boldsymbol{W}; \theta, \ell, m, r) = \Big(Y - \ell(\boldsymbol{X}) - \theta(D - m(\boldsymbol{X}))\Big)\Big(Z - r(\boldsymbol{X})\Big),$$

where $\boldsymbol{W} \equiv (Y, D, \boldsymbol{X}, Z)$.

DDML models

The DDML framework can be applied to other models (all implemented in `ddml`):

Flexible Partially-Linear IV Model

$$Y = \theta_0 D + g_0(\boldsymbol{X}) + U,$$

where we leverage instrumental variables $\boldsymbol{Z}$ for identification.

Let $p_0(\boldsymbol{Z}, \boldsymbol{X}) \equiv E[D|\boldsymbol{Z}, \boldsymbol{X}]$.

We assume $E[U|\boldsymbol{Z}, \boldsymbol{X}] = 0$ and $E[Var(E[D|\boldsymbol{Z}, \boldsymbol{X}]|\boldsymbol{X})] \neq 0$, and consider the score function

$$\psi(\boldsymbol{W}; \theta, \ell, m, p) = \Big(Y - \ell(\boldsymbol{X}) - \theta(D - m(\boldsymbol{X}))\Big)\Big(p(\boldsymbol{Z}, \boldsymbol{X}) - m(\boldsymbol{X})\Big).$$

The Flexible Partially-Linear IV Model allows for approximation of *optimal instruments*.

DDML models

The DDML framework can be applied to other models (all implemented in `ddml`):

Interactive IV model

$$Y = g_0(D, \boldsymbol{X}) + U$$

where D takes values in $\{0, 1\}$. The parameter of interest we target is the *local average treatment effect* (LATE)

$$\theta_0 = E\left[g_0(1, \boldsymbol{X}) - g_0(0, \boldsymbol{X}) \middle| \, p_0(1, \boldsymbol{X}) > p_0(0, \boldsymbol{X})\right], \tag{4}$$

where $p_0(Z, \boldsymbol{X}) \equiv \Pr(D = 1 | Z, \boldsymbol{X})$.

The choice of machine learner

Which machine learner should we use?

`ddml` supports a range of ML programs: `pylearn`, `lassopack`, `randomforest`. — Which one should we use?

We don't know whether we have a sparse or dense problem; linear or non-linear. We don't know whether, e.g., lasso or random forests will perform better.

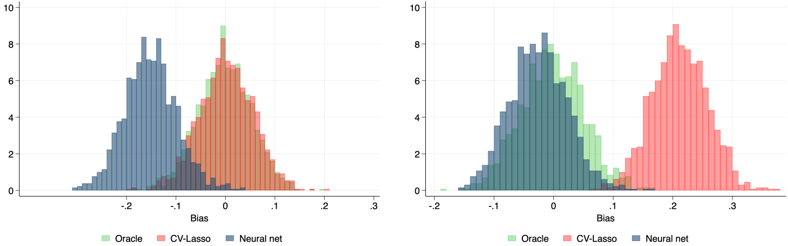
Stacking, as implemented in `pystacked`, provides a solution: We use an 'optimal' combination of base learners.

The choice of machine learner

Which machine learner should we use?

The choice of CEF estimator can make a huge difference.

Left: the non-linear learner struggles with the linear DGP.
Right: the linear learner struggles with the non-linear DGP.



(a) Linear DGP

(b) Non-linear DGP

Notes: Figures (a) and (b) compare the bias of the oracle estimator (which knows the true data-generating process), cross-validated lasso and gradient-boosted trees under two alternative data-generating processes. We generate 1'000 samples of size $n = 1000$ using the partially-linear model $Y_i = \theta_0 D_i + g(\boldsymbol{X}_i) + \varepsilon_i$, $D_i = g(\boldsymbol{X}_i) + u_i$ where the nuisance function is either $g(\boldsymbol{X}_i) = \sum_j 0.9^j X_{ij}$ (linear) or $g(\boldsymbol{X}_i) = \mathbb{1}\{X_{i1} > 0.3\}\mathbb{1}\{X_{i2} > 0\}\mathbb{1}\{X_{i3} > -1\}$ (non-linear DGP). Gradient boosting uses 1000 trees, a learning rate of 0.01 and early stopping with 20% validation sample. See Ahrens et al. (2023, Section 4.2) for details.

The choice of machine learner

Which machine learner should we use?

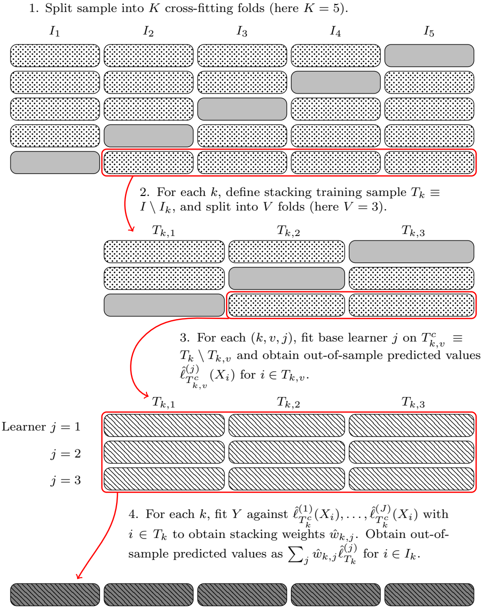
We have already seen one answer: stacking.

DDML + stacking involves two layers of re-sampling:

1. *Cross-fitting (upper) layer:* Divide the sample into K cross-fitting folds. In each cross-fitting step $k \in \{1, \ldots, K\}$, the stacking learner is trained on the training sample $T_k \equiv I \setminus I_k$.
2. *Cross-validation (lower) layer:* Fitting the stacking learner requires subdividing the training sample T_k further into V cross-validation folds. We denote the cross-validation folds by $T_{k,1}, \ldots, T_{k,V}$.

A DDML-specific variant: ‘pooled stacking’, i.e., stack once at the end to get a single stacked learner (a single set of stacking weights instead of K sets of weights).

The choice of machine learner



1. Split sample into K cross-fitting folds (here $K = 5$).

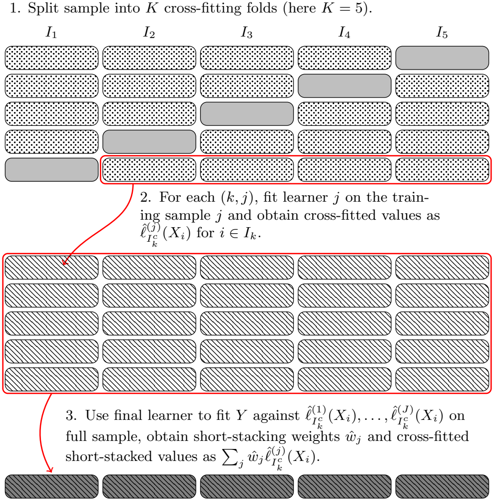
2. For each k, define stacking training sample $T_k \equiv I \setminus I_k$, and split into V folds (here $V = 3$).

3. For each (k, v, j), fit base learner j on $T^c_{k,v} \equiv T_k \setminus T_{k,v}$ and obtain out-of-sample predicted values $\hat{\ell}^{(j)}_{T^c_{k,v}}(X_i)$ for $i \in T_{k,v}$.

4. For each k, fit Y against $\hat{\ell}^{(1)}_{T^c_k}(X_i), \dots, \hat{\ell}^{(J)}_{T^c_k}(X_i)$ with $i \in T_k$ to obtain stacking weights $\hat{w}_{k,j}$. Obtain out-of-sample predicted values as $\sum_j \hat{w}_{k,j} \hat{\ell}^{(j)}_{T_k}$ for $i \in I_k$.

The choice of machine learner

Short-stacking takes a short-cut and is computationally much cheaper. The final learner is fit on the cross-fitted predicted values.



1. Split sample into K cross-fitting folds (here $K = 5$).

2. For each (k, j), fit learner j on the training sample j and obtain cross-fitted values as $\hat{\ell}^{(j)}_{I_k^c}(X_i)$ for $i \in I_k$.

3. Use final learner to fit Y against $\hat{\ell}^{(1)}_{I_k^c}(X_i), \ldots, \hat{\ell}^{(J)}_{I_k^c}(X_i)$ on full sample, obtain short-stacking weights $\hat{w}_j$ and cross-fitted short-stacked values as $\sum_j \hat{w}_j \hat{\ell}^{(j)}_{I_k^c}(X_i)$.

The `ddml` package

We introduce `ddml` for Stata:

- Compatible with various ML programs in Stata (e.g. `lassopack`, `pylearn`, `randomforest`).
  - → *Any* program with the classical "`reg y x`" syntax and post-estimation `predict` will work.
- Short (one-line) and flexible multi-line version
- Five models supported: partially-linear model, interactive model, interactive IV model, partially-linear IV model, flexible partially-linear IV.
- `ddml` supports data-driven combinations of multiple machine learners via stacking by leveraging `pystacked` (Ahrens, Hansen, and Schaffer, 2022; Pedregosa et al., 2011; Buitinck et al., 2013).
- Standard stacking, short-stacking, pooled stacking all supported.
- Forthcoming `ddml` paper in *The Stata Journal* (working paper version: Ahrens, Hansen, and Schaffer (2022)).

Extended ddml syntax

Step 1: Initialize `ddml` and select model.

```
ddml init model [, kfolds(integer) fcluster(varname)
foldvar(varlist) reps(integer) mname(name) prefix ]
```

where *model* is `partial`, `interactive`, `iv`, `fiv`, or `interactiveiv`.

The `reps` option repeats the estimation for the specified number of different random cross-fit splits. In this case `ddml` will report the median or mean estimated coefficient(s) of interest across resamples.

Step 2: Add ML programs for estimating conditional expectations.

```
ddml cond_exp :  command depvar vars [, cmdopt ]
```

where *cond_exp* selects the conditional expectation to be estimated by the machine learning program *command*. *command* is a ML program that supports the standard `reg y x`-type syntax. *cmdopt* are specific to that program.

Multiple estimation commands per equation are allowed.

Extended ddml syntax

cond_exp	`partial`	`interactive`	`iv`	`fiv`	`late`
`E[Y|X]`	✓		✓	✓	
`E[Y|X,D]`		✓			
`E[Y|X,Z]`					✓
`E[D|X]`	✓	✓	✓	✓	
`E[D|Z,X]`				✓	✓
`E[Z|X]`			✓		✓

Table: The table lists the conditional expectations which need to be specified for each model.

Extended `ddml` syntax

Step 3: Cross-fitting.

This step implements the cross-fitting algorithm (the most time-consuming step).

```
ddml crossfit [, mname(name) shortstack poolstack
nostdstack finalest(name) ]
```

Standard stacking and pooled-stacking rely on `ddml`'s `pystacked` integration; short-stacking is available with all learners.

Step 4: Estimation of causal effects

In the last step, we estimate the parameter of interest for all combination of learners added in Step 2.

```
ddml estimate [, mname(name) robust cluster(varname)
vce(vcetype) att trim spec(string) rep(string) ]
```

Quick syntax: `qddml`

Syntax for Partially-Linear and Interactive Model

`qddml` *depvar treatment_vars* (*controls*),
`model(partial|interactive)` [*options*]

Syntax for IV models

`qddml` *depvar* (*controls*) (*treatment_vars*=*excluded_instruments*) ,
`model(iv|late|fiv)` [*options*]

where *ddml_options* options are internally passed to the `ddml` subroutines.

We illustrate with a `qddml` at the end of this presentation.

Simple `ddml` example

We demonstrate the use of `ddml` using the partially-linear model by extending the analysis of 401(k) eligibility and total financial wealth of Poterba, Venti, and Wise (1995). The data consists of $n = 9915$ households from the 1991 SIPP.

In this simple example, we use two learners, OLS and cross-validated lasso. This gives us 4 possible combinations of learners for Y and D; `ddml` will report all 4 and the minimum-MSE specification in detail.

Step 0: Load data, define globals

```
. use "sipp1991.dta", clear

. global Y net_tfa

. global X age inc educ fsize marr twoearn db pira hown

. global D e401
```

Step 1: Initialise `ddml` and select model:

```
. set seed 123

. ddml init partial, kfolds(4)
```

Simple `ddml` example (cont'd.)

Step 2: Add supervised ML programs for estimating conditional expectations. We used `pystacked` as the front-end for sklearn.linear_model.LassoCV.

```
. *** add learners for E[Y|X]
. ddml E[Y|X]: reg $Y $X
Learner Y1_reg added successfully.

. ddml E[Y|X]: pystacked $Y c.($X)##c.($X), type(reg) m(lassocv)
Learner Y2_pystacked added successfully.

. *** add learners for E[D|X]
. ddml E[D|X]: reg $D $X
Learner D1_reg added successfully.

. ddml E[D|X]: pystacked $D c.($X)##c.($X), type(reg) m(lassocv)
Learner D2_pystacked added successfully.
```

Step 3: Cross-fitting with 4 folds

```
. ddml crossfit
Cross-fitting E[y|X] equation: net_tfa
Cross-fitting fold 1 2 3 4 ...completed cross-fitting
Cross-fitting E[D|X] equation: e401
Cross-fitting fold 1 2 3 4 ...completed cross-fitting
```

Simple `ddml` example (cont'd.)

Step 4: Estimation of causal effects

```
. ddml estimate, robust allcombos

Model:                    partial, crossfit folds k=4, resamples r=1
Mata global (mname):      m0
Dependent variable (Y): net_tfa
 net_tfa learners:        Y1_reg Y2_pystacked
D equations (1):          e401
 e401 learners:           D1_reg D2_pystacked

DDML estimation results:
spec  r     Y learner     D learner         b        SE
   1  1        Y1_reg        D1_reg  5986.657 (1523.694)
   2  1        Y1_reg  D2_pystacked  9563.875 (1389.172)
   3  1  Y2_pystacked        D1_reg  9175.519 (1371.065)
*  4  1  Y2_pystacked  D2_pystacked  9788.291 (1339.797)
* = minimum MSE specification for that resample.

Min MSE DDML model
y-E[y|X]  = y-Y2_pystacked_1                        Number of obs   =      9915
D-E[D|X]  = D-D2_pystacked_1
------------------------------------------------------------------------------
             |               Robust
     net_tfa | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        e401 |   9788.291   1339.797     7.31   0.000     7162.337    12414.24
       _cons |   90.93481   534.8139     0.17   0.865    -957.2813    1139.151
------------------------------------------------------------------------------
```

Extended `ddml` example

We use the same dataset and model as before, but employ stacking with a wider range of learner. `pystacked` does the standard stacking; `ddml` does the short-stacking and pooled stacking.

We could ask for all versions of stacking at the cross-fitting stage. Instead, for illustration purposes, we first estimate using only standard stacking and then re-stack to get the short-stacking and pooled stacking results (re-stacking is very fast).

Step 0: Load data, define globals

```
. use "sipp1991.dta", clear

. global Y net_tfa

. global X age inc educ fsize marr twoearn db pira hown

. global D e401
```

Step 1: Initialise `ddml` and select model:

```
. set seed 123

. ddml init partial, kfolds(4)
warning - model m0 already exists
all existing model results and variables will
```

Extended `ddml` example (cont'd.)

Step 2: Add supervised ML programs for estimating conditional expectations.

```
. *** add learners for E[Y|X]
. ddml E[Y|X]: pystacked $Y $X                                          || ///
>     method(ols)                                                        || ///
>     m(lassocv) xvars(c.($X)##c.($X))                                   || ///
>     m(ridgecv) xvars(c.($X)##c.($X))                                   || ///
>     m(rf) pipe(sparse) opt(max_features(5))                            || ///
>     m(gradboost) pipe(sparse) opt(n_estimators(250) learning_rate(0.01)) ,  ///
>     njobs(5)
Learner Y1_pystacked added successfully.
. *** add learners for E[D|X]
. ddml E[D|X]: pystacked $D $X                                          || ///
>     method(ols)                                                        || ///
>     m(lassocv) xvars(c.($X)##c.($X))                                   || ///
>     m(ridgecv) xvars(c.($X)##c.($X))                                   || ///
>     m(rf) pipe(sparse) opt(max_features(5))                            || ///
>     m(gradboost) pipe(sparse) opt(n_estimators(250) learning_rate(0.01)) ,  ///
>     njobs(5)
Learner D1_pystacked added successfully.
```

Extended `ddml` example (cont'd.)

Step 3: Cross-fitting with 4 folds; also report stacking weights

```
. qui ddml crossfit

. ddml extract, show(stweights)

mean stacking weights across folds/resamples for D1_pystacked (e401)
final stacking estimator: nnls1
               learner  mean_weight        rep_1
      ols            1    .01557419    .01557419
  lassocv            2    .10077907    .10077907
  ridgecv            3    .43674242    .43674242
       rf            4    .02946916    .02946916
gradboost            5    .41743516    .41743516

mean stacking weights across folds/resamples for Y1_pystacked (net_tfa)
final stacking estimator: nnls1
               learner  mean_weight        rep_1
      ols            1    .09662631    .09662631
  lassocv            2    .46475744    .46475744
  ridgecv            3    .32388159    .32388159
       rf            4    .09392877    .09392877
gradboost            5     .0145518     .0145518
```

Note that these are **mean** weights across 4 cross-fits.

Extended `ddml` example (cont'd.)

Step 4: Estimation of causal effects - standard stacking only

```
. ddml estimate, robust

Model:                  partial, crossfit folds k=4, resamples r=1
Mata global (mname):    m0
Dependent variable (Y): net_tfa
 net_tfa learners:      Y1_pystacked
D equations (1):        e401
 e401 learners:         D1_pystacked

DDML estimation results:
spec  r     Y learner     D learner         b        SE
  st  1  Y1_pystacked  D1_pystacked  9406.385 (1300.170)

Stacking DDML model
y-E[y|X]  = y-Y1_pystacked_1                       Number of obs     =      9915
D-E[D|X]  = D-D1_pystacked_1
------------------------------------------------------------------------------
             |               Robust
     net_tfa | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        e401 |   9406.385    1300.17     7.23   0.000     6858.099    11954.67
       _cons |   199.9921   535.7477     0.37   0.709    -850.0541    1250.038
------------------------------------------------------------------------------

Stacking final estimator: nnls1
```

Extended `ddml` example (cont'd.)

Step 4: Estimation of causal effects - all stacking approaches

```
. ddml estimate, robust shortstack poolstack

Model:                  partial, crossfit folds k=4, resamples r=1
Mata global (mname):    m0
Dependent variable (Y): net_tfa
 net_tfa learners:      Y1_pystacked
D equations (1):        e401
 e401 learners:         D1_pystacked

DDML estimation results:
spec  r     Y learner     D learner         b        SE
  st  1  Y1_pystacked  D1_pystacked  9406.385 (1300.170)
  ss  1  [shortstack]          [ss]  9602.257 (1300.825)
  ps  1   [poolstack]          [ps]  9500.180 (1298.057)

Shortstack DDML model
y-E[y|X]  = y-Y_net_tfa_ss_1                      Number of obs   =      9915
D-E[D|X]  = D-D_e401_ss_1
------------------------------------------------------------------------------
             |               Robust
     net_tfa | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        e401 |   9602.257   1300.825     7.38   0.000     7052.686    12151.83
       _cons |   83.96648   533.9871     0.16   0.875    -962.6289    1130.562
------------------------------------------------------------------------------

Stacking final estimator: nnls1
```

Extended `ddml` example (cont'd.)

Step 3: Cross-fitting details - pooled stacking weights

```
. ddml extract, show(psweights)

pool-stacked weights across resamples for e401
final stacking estimator: nnls1
               learner  mean_weight        rep_1
      ols            1    .01402517    .01402517
  lassocv            2    .07247975    .07247975
  ridgecv            3    .45850746    .45850746
       rf            4    .02897607    .02897607
gradboost            5    .42601154    .42601154

pool-stacked weights across resamples for net_tfa
final stacking estimator: nnls1
               learner  mean_weight        rep_1
      ols            1    .07029722    .07029722
  lassocv            2    .54372578    .54372578
  ridgecv            3    .28352699    .28352699
       rf            4    .10245001    .10245001
gradboost            5            0            0
```

Pooled stacking uses a **single** set of weights across 4 cross-fits.

Extended `ddml` example (cont'd.)

Step 3: Cross-fitting details - short-stacking weights

```
. ddml extract, show(ssweights)
short-stacked weights across resamples for e401
final stacking estimator: nnls1
              learner  mean_weight        rep_1
      ols           1            0            0
  lassocv           2    .24106979    .24106979
  ridgecv           3    .34172854    .34172854
       rf           4    .05456544    .05456544
gradboost           5    .36263623    .36263623
short-stacked weights across resamples for net_tfa
final stacking estimator: nnls1
              learner  mean_weight        rep_1
      ols           1    .07689168    .07689168
  lassocv           2            0            0
  ridgecv           3    .79121732    .79121732
       rf           4            0            0
gradboost           5      .131891      .131891
```

Short-stacking uses a **single** set of weights. Standard stacking is not required so estimation using just short-stacking is fast.

`qddml` example: partially-linear model

`qddml` is the one-line ('quick') version of `ddml` and uses a syntax similar to `pds/ivlasso`.

The `qddml` default when used with `pystacked` is to do short-stacking only (much faster than standard stacking).

NB: This can also be done with `ddml`- use the `nostdstack` option at the cross-fit stage.

Here is how to do the same DDML estimation in one line using `qddml`. We choose a different model name for the Mata object and use the `prefix` option so the estimated model and conditional expectations in Stata's memory don't overwrite those from the previous estimation.

NB: All `ddml` postestimation commands and utilities also work after `qddml`. Below we illustrate the use of the `replay` option of `ddml estimate`.

`qddml` example: partially-linear model (cont'd.)

```
. global pystacked_opts                                                      || ///
>     method(ols)                                                            || ///
>     m(lassocv) xvars(c.($X)##c.($X))                                       || ///
>     m(ridgecv) xvars(c.($X)##c.($X))                                       || ///
>     m(rf) pipe(sparse) opt(max_features(5))                                || ///
>     m(gradboost) pipe(sparse) opt(n_estimators(250) learning_rate(0.01)) ,  ///
>     njobs(5)

.
. set seed 123

. // suppress output with quietly
. qui qddml $Y $D ($X), model(partial) kfolds(4) robust   ///
>         pystacked($pystacked_opts)

.
. // illustrate replay option
. ddml estimate, spec(ss) rep(1) notable replay

Shortstack DDML model
y-E[y|X]  = y-Y_net_tfa_ss_1                      Number of obs   =      9915
D-E[D|X]  = D-D_e401_ss_1
------------------------------------------------------------------------------
             |               Robust
     net_tfa | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
        e401 |   9602.257   1300.825     7.38   0.000     7052.686    12151.83
       _cons |   83.96648   533.9871     0.16   0.875    -962.6289    1130.562
------------------------------------------------------------------------------

Stacking final estimator:
```

Summary

- `ddml` implements Double/Debiased Machine Learning for Stata:
  - Compatible with various ML programs in Stata
  - Short (one-line) and flexible multi-line version
  - Uses Stacking Regression as the default machine learner; implemented via separate program `pystacked`
  - 5 models supported
- The advantage to `pdslasso` is that we can make use of almost any machine learner.
- *But which machine learner should we use?*
  - We suggest stacking. We don't know which learner is best suited for a particular problem.
  - Stacking allows to consider multiple learners in a joint framework, and thus reduces the risk of misspecification.
  - `ddml` supports 3 forms of stacking: standard stacking, short-stacking and pooled stacking. NB: Our MC results (separate paper) suggest short-stacking performs as well or better than the other two versions and is much faster; our recommended default.

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