

# Package: MetaIntegration (via r-universe)

October 9, 2024

**Type** Package

**Title** Ensemble Meta-Inference Framework

**Version** 0.1.3

**Description** An ensemble meta-inference framework to integrate multiple regression models into a current study. Gu, T., Taylor, J.M.G. and Mukherjee, B. (2021) <[arXiv:2010.09971](https://arxiv.org/abs/2010.09971)>. A meta-analysis framework along with two weighted estimators as the ensemble of empirical Bayes estimators, which combines the estimates from the different external models. The proposed framework is flexible and robust in the ways that (i) it is capable of incorporating external models that use a slightly different set of covariates; (ii) it is able to identify the most relevant external information and diminish the influence of information that is less compatible with the internal data; and (iii) it nicely balances the bias-variance trade-off while preserving the most efficiency gain. The proposed estimators are more efficient than the naive analysis of the internal data and other naive combinations of external estimators.

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**License** GPL-2

**Encoding** UTF-8

**LazyData** true

**Biarch** true

**Depends** R (>= 3.5.0)

**Imports** Rsolnp, corpcor, MASS, knitr

**URL** <https://github.com/umich-biostatistics/MetaIntegration>

**BugReports** <https://github.com/umich-biostatistics/MetaIntegration/issues>

**RoxygenNote** 7.1.1

**Roxygen** list(markdown = TRUE)

**Repository** <https://umich-biostatistics.r-universe.dev>

**RemoteUrl** <https://github.com/umich-biostatistics/metaintegration>

**RemoteRef** HEAD

**RemoteSha** c7c80d84ded9ea6785b19aafce5f08b42517f284

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asypVar_LinReg	<i>Asymptotic variance-covariance matrix for gamma_Int and gamma_CML for linear regression (continuous outcome Y)</i>
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## Description

Asymptotic variance-covariance matrix for gamma\_Int and gamma\_CML for linear regression (continuous outcome Y)

## Usage

```
asypVar_LinReg(
  k,
  p,
  q,
  YInt,
  XInt,
  BInt,
  gammaHatInt,
  betaHatExt_list,
  CovExt_list,
  rho,
  ExUncertainty
)
```

**Arguments**

k	number of external models
p	total number of X covariates including the intercept (i.e. $p = \text{ncol}(X) + 1$ )
q	total number of covariates including the intercept (i.e. $q = \text{ncol}(X) + \text{ncol}(B) + 1$ )
YInt	Outcome vector
XInt	X covariates that are used in the external models - Do not include intercept
BInt	Newly added B covariates that are not included in the external models
gammaHatInt	Internal parameter estimates of the full model using the internal data
betaHatExt_list	a list of k items, each item is a vector of the external parameter estimates (beta). Vector name is required for each covariate, and has to be as consistent as the full model
CovExt_list	a list of k items, each item is the variance-covariance matrix of the external parameter estimates (beta) of the reduced model
rho	a list of k items, each item is the sample size ratio, $n/m$ (the internal sample size n over the external sample size m)
ExUncertainty	logic indicator, if TRUE then considering the external model uncertainty in the algorithm; if FALSE then ignoring the external model uncertainty

**Value**

a list containing:

- "asyV.I" Variance of  $\gamma_I$  (the direct regression parameter estimates using the internal data only)
- "asyV.CML" Variance of  $\gamma_{CML}$  (the CML estimates (Chatterjee et al. 2016))
- "asyCov.CML" Covariance between two different CML estimates,  $\gamma_{CMLi}$  and  $\gamma_{CMLj}$
- "asyCov.CML.I" Covariance between  $\gamma_I$  and  $\gamma_{CML}$
- "ExtraTerm" the extra variance when  $\text{ExUncertainty} == \text{TRUE}$  (i.e. the external uncertainty is considered in the algorithm)

**References**

Chatterjee, N., Chen, Y.-H., P.Maas and Carroll, R. J. (2016). Constrained maximum likelihood estimation for model calibration using summary-level information from external big data sources. *Journal of the American Statistical Association* 111, 107-117.

Gu, T., Taylor, J.M.G. and Mukherjee, B. (2020). An ensemble meta-prediction framework to integrate multiple regression models into a current study. Manuscript in preparation.

**Examples**

```
# Full model: Y|X1, X2, B
# Reduced model 1: Y|X1 of sample size m1
# Reduced model 2: Y|X2 of sample size m2
# (X1, X2, B) follows normal distribution with mean zero, variance one and correlation 0.3
```

```

# Y|X1, X2, B follows  $N(-1-0.5*X1-0.5*X2+0.5*B, 1)$ 
set.seed(2333)
n = 1000
data.n = data.frame(matrix(ncol = 4, nrow = n))
colnames(data.n) = c('Y', 'X1', 'X2', 'B')
data.n[,c('X1', 'X2', 'B')] = MASS::mvrnorm(n, rep(0,3), diag(0.7,3)+0.3)
data.n$Y = rnorm(n, -1 - 0.5*data.n$X1 - 0.5*data.n$X2 + 0.5*data.n$B, 1)

# Generate the beta estimates from the external reduced model:
# generate a data of size m from the full model first, then fit the reduced regression
# to obtain the beta estimates and the corresponding estimated variance
m = m1 = m2 = 30000
data.m = data.frame(matrix(ncol = 4, nrow = m))
names(data.m) = c('Y', 'X1', 'X2', 'B')
data.m[,c('X1', 'X2', 'B')] = MASS::mvrnorm(m, rep(0,3), diag(0.7,3)+0.3)
data.m$Y = rnorm(m, -1 - 0.5*data.m$X1 - 0.5*data.m$X2 + 0.5*data.m$B, 1)

#fit Y|X to obtain the external beta estimates, save the beta estimates and the
# corresponding estimated variance
fit.E1 = lm(Y ~ X1, data = data.m)
fit.E2 = lm(Y ~ X2, data = data.m)
beta.E1 = coef(fit.E1)
beta.E2 = coef(fit.E2)
names(beta.E1) = c('int', 'X1')
names(beta.E2) = c('int', 'X2')
V.E1 = vcov(fit.E1)
V.E2 = vcov(fit.E2)

#Save all the external model information into lists for later use
betaHatExt_list = list(Ext1 = beta.E1, Ext2 = beta.E2)
CovExt_list = list(Ext1 = V.E1, Ext2 = V.E2)
rho = list(Ext1 = n/m1, Ext2 = n/m2)

#get full model estimate from direct regression using the internal data only
fit.gamma.I = lm(Y ~ X1 + X2 + B, data = data.n)
gamma.I = coef(fit.gamma.I)

#Get CML estimates using internal data and the beta estimates from the external
# model 1 and 2, respectively
gamma.CML1 = fxnCC_LinReg(p=2, q=4, YInt=data.n$Y, XInt=data.n$X1,
                        BInt=cbind(data.n$X2, data.n$B), betaHatExt=beta.E1,
                        gammaHatInt=gamma.I, n=nrow(data.n), tol=1e-8,
                        maxIter=400, factor=1)[["gammaHat"]]
gamma.CML2 = fxnCC_LinReg(p=2, q=4, YInt=data.n$Y, XInt=data.n$X2,
                        BInt=cbind(data.n$X1, data.n$B), betaHatExt=beta.E2,
                        gammaHatInt=gamma.I, n=nrow(data.n), tol=1e-8,
                        maxIter=400, factor=1)[["gammaHat"]]

#It's important to reorder gamma.CML2 so that it follows the order (X1, X2, X3, B)
# as gamma.I and gamma.CML1
gamma.CML2 = c(gamma.CML2[1], gamma.CML2[3], gamma.CML2[2], gamma.CML2[4])

#Get Variance-covariance matrix of c(gamma.I, gamma.CML1, gamma.CML2)
asy.CML = asympVar_LinReg(k=2,

```

```

        p=2,
        q=4,
        YInt=data.n$Y,
        XInt=data.n[,c('X1','X2')],
        #covariates that appeared in at least one external model
        BInt=data.n$B, #covariates that not used in any of the external models
        gammaHatInt=gamma.I,
        betaHatExt_list=betaHatExt_list,
        CovExt_list=CovExt_list,
        rho=rho,
        ExUncertainty=TRUE)
asyV.I = asy.CML[["asyV.I"]] #variance of gamma.I
asyV.CML1 = asy.CML[["asyV.CML"]][[1]] #variance of gamma.CML1
asyV.CML2 = asy.CML[["asyV.CML"]][[2]] #variance of gamma.CML2
asyCov.CML1.I = asy.CML[["asyCov.CML.I"]][[1]] #covariance of gamma.CML1 and gamma.I
asyCov.CML2.I = asy.CML[["asyCov.CML.I"]][[2]] #covariance of gamma.CML2 and gamma.I
asyCov.CML12 = asy.CML[["asyCov.CML"]][["12"]] #covariance of gamma.CML1 and gamma.CML2

```

---

asympVar_LogReg	<i>Asymptotic variance-covariance matrix for gamma_Int and gamma_CML for logistic regression (binary outcome Y)</i>
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---

### Description

Asymptotic variance-covariance matrix for gamma\_Int and gamma\_CML for logistic regression (binary outcome Y)

### Usage

```

asympVar_LogReg(
  k,
  p,
  q,
  YInt,
  XInt,
  BInt,
  gammaHatInt,
  betaHatExt_list,
  CovExt_list,
  rho,
  ExUncertainty
)

```

### Arguments

k                    number of external models

p	total number of all X covariates that is used at least once in the external model, including the intercept (i.e. $p = \text{ncol}(X) + 1$ )
q	total number of covariates including the intercept (i.e. $q = \text{ncol}(X) + \text{ncol}(B) + 1$ )
YInt	Outcome vector
XInt	X covariates that are used in the external models - Do not include intercept
BInt	Newly added B covariates that are not included in the external models
gammaHatInt	Internal parameter estimates of the full model using the internal data
betaHatExt_list	a list of k items, each item is a vector of the external parameter estimates (beta). Vector name is required for each covariate, and has to be as consistent as the full model
CovExt_list	a list of k items, each item is the variance-covariance matrix of the external parameter estimates (beta) of the reduced model
rho	a list of k items, each item is the sample size ratio, n/m (the internal sample size n over the external sample size m)
ExUncertainty	logic indicator, if TRUE then considering the external model uncertainty in the algorithm; if FALSE then ignoring the external model uncertainty

### Value

a list containing:

- "asyV.I" Variance of gamma\_I (the direct regression parameter estimates using the internal data only)
- "asyV.CML" Variance of gamma\_CML (the CML estimates (Chatterjee et al. 2016))
- "asyCov.CML" Covariance between two different CML estimates, gamma\_CMLi and gamma\_CMLj
- "asyCov.CML.I" Covariance between gamma\_I and gamma\_CML
- "ExtraTerm" the extra variance when ExUncertainty == TRUE (i.e. the external uncertainty is considered in the algorithm)

### References

Chatterjee, N., Chen, Y.-H., P.Maas and Carroll, R. J. (2016). Constrained maximum likelihood estimation for model calibration using summary-level information from external big data sources. *Journal of the American Statistical Association* 111, 107-117.

Gu, T., Taylor, J.M.G. and Mukherjee, B. (2020). An ensemble meta-prediction framework to integrate multiple regression models into a current study. Manuscript in preparation.

### Examples

```
# Full model: Y|X1, X2, B
# Reduced model 1: Y|X1 of sample size m1
# Reduced model 2: Y|X2 of sample size m2
# (X1, X2, B) follows normal distribution with mean zero, variance one and correlation 0.3
# Y|X1, X2, B follows Bernoulli[expit(-1-0.5*X1-0.5*X2+0.5*B)], where expit(x)=exp(x)/[1+exp(x)]
set.seed(2333)
```



```

      YInt=data.n$Y,
      XInt=data.n[,c('X1','X2')], #covariates that appeared
      # in at least one external model
      BInt=data.n$B, #covariates that not used in any of the external models
      gammaHatInt=gamma.I,
      betaHatExt_list=betaHatExt_list,
      CovExt_list=CovExt_list,
      rho=rho,
      ExUncertainty=TRUE)
asyV.I = asy.CML[["asyV.I"]] #variance of gamma.I
asyV.CML1 = asy.CML[["asyV.CML"]][[1]] #variance of gamma.CML1
asyV.CML2 = asy.CML[["asyV.CML"]][[2]] #variance of gamma.CML2
asyCov.CML1.I = asy.CML[["asyCov.CML.I"]][[1]] #covariance of gamma.CML1 and gamma.I
asyCov.CML2.I = asy.CML[["asyCov.CML.I"]][[2]] #covariance of gamma.CML2 and gamma.I
asyCov.CML12 = asy.CML[["asyCov.CML"]][["12"]] #covariance of gamma.CML1 and gamma.CML2

```

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 expit

*Expit*


---

## Description

Standard expit function

## Usage

```
expit(x)
```

## Arguments

x                    data to transform

## Details

$$y = \exp(x) / (1 + \exp(x))$$

## Value

vector of transformed data



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fxnCC_LinReg	<i>Constraint maximum likelihood (CML) method for linear regression (continuous outcome Y)</i>
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**Description**

Constraint maximum likelihood (CML) method for linear regression (continuous outcome Y)

**Usage**

```
fxnCC_LinReg(
  p,
  q,
  YInt,
  XInt,
  BInt,
  betaHatExt,
  gammaHatInt,
  n,
  tol,
  maxIter,
  factor
)
```

**Arguments**

p	total number of X covariates including the intercept (i.e. $p = \text{ncol}(X) + 1$ )
q	total number of covariates including the intercept (i.e. $q = \text{ncol}(X) + \text{ncol}(B) + 1$ )
YInt	Outcome vector
XInt	X covariates that are used in the external models - Do not include intercept
BInt	Newly added B covariates that are not included in the external models
betaHatExt	External parameter estimates of the reduced model
gammaHatInt	Full model parameter estimates using the internal data only
n	internal data sample size
tol	convergence criteria e.g. $1e-6$
maxIter	Maximum number of iterations to reach convergence e.g. 400
factor	the step-halving factor between 0 and 1, if factor=1 then newton-raphson method; decrease if algorithm cannot converge given the maximum iterations

**Value**

gammaHat, in the order (intercept, XInt, BInt)

## References

Chatterjee, N., Chen, Y.-H., P.Maas and Carroll, R. J. (2016). Constrained maximum likelihood estimation for model calibration using summary-level information from external big data sources. *Journal of the American Statistical Association* 111, 107-117.

## Examples

```
# Full model: Y|X, B
# Reduced model: Y|X
# X,B follows normal distribution with mean zero, variance one and correlation 0.3
# Y|X, B follows N(-1-0.5X+0.5B, 1)
set.seed(2333)
n = 800
data.n = data.frame(matrix(ncol = 3, nrow = n))
colnames(data.n) = c('Y', 'X', 'B')
data.n[,c('X', 'B')] = MASS::mvrnorm(n, rep(0,2), diag(0.7,2)+0.3)
data.n$Y = rnorm(n, -1 - 0.5*data.n$X + 0.5*data.n$B, 1)

# Generate the beta estimates from the external reduced model:
# generate a data of size m from the full model first, then fit the reduced regression
# to obtain the beta estimates and the corresponding estimated variance
m = 30000
data.m = data.frame(matrix(ncol = 3, nrow = m))
names(data.m) = c('Y', 'X', 'B')
data.m[,c('X', 'B')] = MASS::mvrnorm(m, rep(0,2), diag(0.7,2)+0.3)
data.m$Y = rnorm(m, -1 - 0.5*data.m$X + 0.5*data.m$B, 1)

#fit Y|X to obtain the external beta estimates, save the beta estimates and the
# corresponding estimated variance
fit.E = lm(Y ~ X, data = data.m)
beta.E = coef(fit.E)
names(beta.E) = c('int', 'X')
V.E = vcov(fit.E)

#get full model estimate from direct regression using the internal data only
fit.gamma.I = lm(Y ~ X + B, data = data.n)
gamma.I = coef(fit.gamma.I)

#Get CML estimates
gamma.CML = fxnCC_LinReg(p=2,
                        q=3,
                        YInt=data.n$Y,
                        XInt=data.n[, 'X'],
                        BInt=data.n[, 'B'],
                        betaHatExt=beta.E,
                        gammaHatInt=gamma.I,
                        n=nrow(data.n),
                        tol=1e-8,
                        maxIter=400,
                        factor=1)[["gammaHat"]]
```

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fxnCC_LogReg	<i>Constraint maximum likelihood (CML) method for logistic regression (binary outcome Y)</i>
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**Description**

Constraint maximum likelihood (CML) method for logistic regression (binary outcome Y)

**Usage**

```
fxnCC_LogReg(
  p,
  q,
  YInt,
  XInt,
  BInt,
  betaHatExt,
  gammaHatInt,
  n,
  tol,
  maxIter,
  factor
)
```

**Arguments**

p	total number of X covariates including the intercept (i.e. $p = \text{ncol}(X) + 1$ )
q	total number of covariates including the intercept (i.e. $q = \text{ncol}(X) + \text{ncol}(B) + 1$ )
YInt	Outcome vector
XInt	X covariates that are used in the external models - Do not include intercept
BInt	Newly added B covariates that are not included in the external models
betaHatExt	External parameter estimates of the reduced model
gammaHatInt	Full model parameter estimates using the internal data only
n	internal data sample size
tol	convergence criteria e.g. $1e-6$
maxIter	Maximum number of iterations to reach convergence e.g. 400
factor	the step-halving factor between 0 and 1, if factor=1 then newton-raphson method; decrease if algorithm cannot converge given the maximum iterations

**Value**

gammaHat, in the order (intercept, XInt, BInt)

## References

Chatterjee, N., Chen, Y.-H., P.Maas and Carroll, R. J. (2016). Constrained maximum likelihood estimation for model calibration using summary-level information from external big data sources. *Journal of the American Statistical Association* 111, 107-117.

## Examples

```
# Full model: Y|X, B
# Reduced model: Y|X
# X,B follows normal distribution with mean zero, variance one and correlation 0.3
# Y|X, B follows N(-1-0.5X+0.5B, 1)
set.seed(2333)
n = 1000
data.n = data.frame(matrix(ncol = 3, nrow = n))
colnames(data.n) = c('Y', 'X', 'B')
data.n[,c('X', 'B')] = MASS::mvrnorm(n, rep(0,2), diag(0.7,2)+0.3)
data.n$Y = rbinom(n, 1, expit(-1 - 0.5*data.n$X + 0.5*data.n$B))

# Generate the beta estimates from the external reduced model:
# generate a data of size m from the full model first, then fit the reduced regression
# to obtain the beta estimates and the corresponding estimated variance
m = 30000
data.m = data.frame(matrix(ncol = 3, nrow = m))
names(data.m) = c('Y', 'X', 'B')
data.m[,c('X', 'B')] = MASS::mvrnorm(m, rep(0,2), diag(0.7,2)+0.3)
data.m$Y = rbinom(m, 1, expit(-1 - 0.5*data.m$X + 0.5*data.m$B))

#fit Y|X to obtain the external beta estimates, save the beta estimates and the
# corresponding estimated variance
fit.E = glm(Y ~ X, data = data.m, family = binomial(link='logit'))
beta.E = coef(fit.E)
names(beta.E) = c('int', 'X')
V.E = vcov(fit.E)

#get full model estimate from direct regression using the internal data only
fit.gamma.I = glm(Y ~ X + B, data = data.n, family = binomial(link='logit'))
gamma.I = coef(fit.gamma.I)

#Get CML estimates
gamma.CML = fxnCC_LogReg(p=2,
                        q=3,
                        YInt=data.n$Y,
                        XInt=data.n$X,
                        BInt=data.n[, 'B'],
                        betaHatExt=beta.E,
                        gammaHatInt=gamma.I,
                        n=nrow(data.n),
                        tol=1e-8,
                        maxIter=400,
                        factor=1)[["gammaHat"]]
```

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get_gamma_EB	<i>Calculate the empirical Bayes (EB) estimates</i>
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**Description**

Calculate the empirical Bayes (EB) estimates

**Usage**

```
get_gamma_EB(gamma_I, gamma_CML, asyV.I)
```

**Arguments**

gamma_I	Full model parameter estimates using the internal data only (MLE from direct regression)
gamma_CML	Full model parameter estimates using the internal data and the external reduced model parameters (Chatterjee et al. 2016)
asyV.I	Variance-covariance matrix of gamma_I from function <code>asympVar_LinReg()</code> or <code>asympVar_LogReg()</code>

**Value**

a list with:

- "gamma\_I" Full model parameter estimates using the internal data only (MLE from direct regression)
- "gamma\_CML" Full model parameter estimates using the internal data and the external reduced model parameters (Chatterjee et al. 2016)
- "gamma\_EB" The empirical Bayes estimate of the full model (i.e. a weighted average of gamma\_I and gamma\_CML) (Estes et al. 2017)

**References**

# Chatterjee, N., Chen, Y.-H., P.Maas and Carroll, R. J. (2016). Constrained maximum likelihood estimation for model calibration using summary-level information from external big data sources. *Journal of the American Statistical Association* 111, 107-117.

Gu, T., Taylor, J.M.G. and Mukherjee, B. (2020). An ensemble meta-prediction framework to integrate multiple regression models into a current study. Manuscript in preparation.

**Examples**

```
# Full model: Y|X1, X2, B
# Reduced model 1: Y|X1 of sample size m1
# Reduced model 2: Y|X2 of sample size m2
# (X1, X2, B) follows normal distribution with mean zero, variance one and
# correlation 0.3
# Y|X1, X2, B follows Bernoulli[expit(-1-0.5*X1-0.5*X2+0.5*B)],
```

```

# where expit(x)=exp(x)/[1+exp(x)]
set.seed(2333)
n = 1000
data.n = data.frame(matrix(ncol = 4, nrow = n))
colnames(data.n) = c('Y', 'X1', 'X2', 'B')
data.n[,c('X1', 'X2', 'B')] = MASS::mvrnorm(n, rep(0,3), diag(0.7,3)+0.3)
data.n$Y = rbinom(n, 1, expit(-1 - 0.5*data.n$X1 - 0.5*data.n$X2 + 0.5*data.n$B))

# Generate the beta estimates from the external reduced model:
# generate a data of size m from the full model first, then fit the reduced regression
# to obtain the beta estimates and the corresponding estimated variance
m = m1 = m2 = 30000
data.m = data.frame(matrix(ncol = 4, nrow = m))
names(data.m) = c('Y', 'X1', 'X2', 'B')
data.m[,c('X1', 'X2', 'B')] = MASS::mvrnorm(m, rep(0,3), diag(0.7,3)+0.3)
data.m$Y = rbinom(m, 1, expit(-1 - 0.5*data.m$X1 - 0.5*data.m$X2 + 0.5*data.m$B))

#fit Y|X to obtain the external beta estimates, save the beta estimates and the
# corresponding estimated variance
fit.E1 = glm(Y ~ X1, data = data.m, family = binomial(link='logit'))
fit.E2 = glm(Y ~ X2, data = data.m, family = binomial(link='logit'))
beta.E1 = coef(fit.E1)
beta.E2 = coef(fit.E2)
names(beta.E1) = c('int', 'X1')
names(beta.E2) = c('int', 'X2')
V.E1 = vcov(fit.E1)
V.E2 = vcov(fit.E2)

#Save all the external model information into lists for later use
betaHatExt_list = list(Ext1 = beta.E1, Ext2 = beta.E2)
CovExt_list = list(Ext1 = V.E1, Ext2 = V.E2)
rho = list(Ext1 = n/m1, Ext2 = n/m2)

#get full model estimate from direct regression using the internal data only
fit.gamma.I = glm(Y ~ X1 + X2 + B, data = data.n, family = binomial(link='logit'))
gamma.I = coef(fit.gamma.I)

#Get CML estimates using internal data and the beta estimates from the external
# model 1 and 2, respectively
gamma.CML1 = fxnCC_LogReg(p=2, q=4, YInt=data.n$Y, XInt=data.n$X1,
                          BInt=cbind(data.n$X2, data.n$B), betaHatExt=beta.E1,
                          gammaHatInt=gamma.I, n=nrow(data.n), tol=1e-8,
                          maxIter=400, factor=1)[["gammaHat"]]
gamma.CML2 = fxnCC_LogReg(p=2, q=4, YInt=data.n$Y, XInt=data.n$X2,
                          BInt=cbind(data.n$X1, data.n$B), betaHatExt=beta.E2,
                          gammaHatInt=gamma.I, n=nrow(data.n), tol=1e-8,
                          maxIter=400, factor=1)[["gammaHat"]]

#It's important to reorder gamma.CML2 so that it follows the order (X1, X2, X3, B)
# as gamma.I and gamma.CML1
gamma.CML2 = c(gamma.CML2[1], gamma.CML2[3], gamma.CML2[2], gamma.CML2[4])

#Get Variance-covariance matrix of c(gamma.I, gamma.CML1, gamma.CML2)
asy.CML = asympVar_LogReg(k=2, p=2,q=4, YInt=data.n$Y, XInt=data.n[,c('X1', 'X2')],

```

```

        BInt=data.n$B, gammaHatInt=gamma.I,
        betaHatExt_list=betaHatExt_list, CovExt_list=CovExt_list,
        rho=rho, ExUncertainty=TRUE)
asyV.I = asy.CML[["asyV.I"]]

#Get the empirical Bayes (EB) estimates
gamma.EB1 = get_gamma_EB(gamma_I=gamma.I, gamma_CML=gamma.CML1, asyV.I=asyV.I)[['gamma.EB']]
gamma.EB2 = get_gamma_EB(gamma_I=gamma.I, gamma_CML=gamma.CML2, asyV.I=asyV.I)[['gamma.EB']]

```

---

get\_OCW

---

*Obtain the proposed Optimal Covariate-Weighted (OCW) estimates*


---

### Description

Obtain the proposed Optimal Covariate-Weighted (OCW) estimates

### Usage

```
get_OCW(k, q, data.XB, gamma.EB, V.EB)
```

### Arguments

k	number of external models
q	total number of covariates (X,B) including the intercept (i.e. $q = \text{ncol}(X) + \text{ncol}(B) + 1$ )
data.XB	internal data (X,B)
gamma.EB	stack all k EB estimates in order, i.e. $c(\text{gamma.EB1}, \dots, \text{gamma.EBk})$
V.EB	variance-covariance matrix obtained from function <code>get_var_EB()</code>

### Value

return weights of gamma.EB's, final estimates of OCW estimates and the corresponding variance-covariance matrix

### References

Reference: Gu, T., Taylor, J.M.G. and Mukherjee, B. (2020). An ensemble meta-prediction framework to integrate multiple regression models into a current study. Manuscript in preparation.

### Examples

```

# Full model: Y|X1, X2, B
# Reduced model 1: Y|X1 of sample size m1
# Reduced model 2: Y|X2 of sample size m2
# (X1, X2, B) follows normal distribution with mean zero, variance one and correlation 0.3
# Y|X1, X2, B follows Bernoulli[expit(-1-0.5*X1-0.5*X2+0.5*B)], where expit(x)=exp(x)/[1+exp(x)]
set.seed(2333)

```

```

n = 1000
data.n = data.frame(matrix(ncol = 4, nrow = n))
colnames(data.n) = c('Y', 'X1', 'X2', 'B')
data.n[,c('X1', 'X2', 'B')] = MASS::mvrnorm(n, rep(0,3), diag(0.7,3)+0.3)
data.n$Y = rbinom(n, 1, expit(-1 - 0.5*data.n$X1 - 0.5*data.n$X2 + 0.5*data.n$B))

# Generate the beta estimates from the external reduced model:
# generate a data of size m from the full model first, then fit the reduced regression
# to obtain the beta estimates and the corresponding estimated variance
m = m1 = m2 = 30000
data.m = data.frame(matrix(ncol = 4, nrow = m))
names(data.m) = c('Y', 'X1', 'X2', 'B')
data.m[,c('X1', 'X2', 'B')] = MASS::mvrnorm(m, rep(0,3), diag(0.7,3)+0.3)
data.m$Y = rbinom(m, 1, expit(-1 - 0.5*data.m$X1 - 0.5*data.m$X2 + 0.5*data.m$B))

#fit Y|X to obtain the external beta estimates, save the beta estimates and
# the corresponding estimated variance
fit.E1 = glm(Y ~ X1, data = data.m, family = binomial(link='logit'))
fit.E2 = glm(Y ~ X2, data = data.m, family = binomial(link='logit'))
beta.E1 = coef(fit.E1)
beta.E2 = coef(fit.E2)
names(beta.E1) = c('int', 'X1')
names(beta.E2) = c('int', 'X2')
V.E1 = vcov(fit.E1)
V.E2 = vcov(fit.E2)

#Save all the external model information into lists for later use
betaHatExt_list = list(Ext1 = beta.E1, Ext2 = beta.E2)
CovExt_list = list(Ext1 = V.E1, Ext2 = V.E2)
rho = list(Ext1 = n/m1, Ext2 = n/m2)

#get full model estimate from direct regression using the internal data only
fit.gamma.I = glm(Y ~ X1 + X2 + B, data = data.n, family = binomial(link='logit'))
gamma.I = coef(fit.gamma.I)

#Get CML estimates using internal data and the beta estimates from the external
# model 1 and 2, respectively
gamma.CML1 = fxnCC_LogReg(p=2, q=4, YInt=data.n$Y, XInt=data.n$X1,
                          BInt=cbind(data.n$X2, data.n$B), betaHatExt=beta.E1,
                          gammaHatInt=gamma.I, n=nrow(data.n), tol=1e-8,
                          maxIter=400, factor=1)[["gammaHat"]]
gamma.CML2 = fxnCC_LogReg(p=2, q=4, YInt=data.n$Y, XInt=data.n$X2,
                          BInt=cbind(data.n$X1, data.n$B), betaHatExt=beta.E2,
                          gammaHatInt=gamma.I, n=nrow(data.n), tol=1e-8,
                          maxIter=400, factor=1)[["gammaHat"]]

#It's important to reorder gamma.CML2 so that it follows the order
# (X1, X2, X3, B) as gamma.I and gamma.CML1
gamma.CML2 = c(gamma.CML2[1], gamma.CML2[3], gamma.CML2[2], gamma.CML2[4])

#Get Variance-covariance matrix of c(gamma.I, gamma.CML1, gamma.CML2)
asy.CML = asympVar_LogReg(k=2, p=2,q=4, YInt=data.n$Y, XInt=data.n[,c('X1','X2')],
                          BInt=data.n$B, gammaHatInt=gamma.I, betaHatExt_list=betaHatExt_list,
                          CovExt_list=CovExt_list, rho=rho, ExUncertainty=TRUE)

```



```

#Get the empirical Bayes (EB) estimates
gamma.EB1 = get_gamma_EB(gamma.I, gamma.CML1, asy.CML[["asyV.I"]])[["gamma.EB"]]
gamma.EB2 = get_gamma_EB(gamma.I, gamma.CML2, asy.CML[["asyV.I"]])[["gamma.EB"]]

#Get the asymptotic variance of the EB estimates
V.EB = get_var_EB(k=2, q=4, gamma.CML=c(gamma.CML1, gamma.CML2),
                gamma.I = gamma.I, asy.CML=asy.CML, seed=2333, nsim=2000)

#Get the OCW estimates, the corresponding variance-covariance matrix of the
# estimates and the weights of gamma.EB's
get_OCW(k=2,
        q=4,
        data.XB=data.n[,c('X1', 'X2', 'B')],
        gamma.EB=c(gamma.EB1, gamma.EB2),
        V.EB=V.EB)

```

---

get_SCLearner	<i>Obtain the proposed Selective Coefficient-Learner (SC-Learner) estimates</i>
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---

## Description

Obtain the proposed Selective Coefficient-Learner (SC-Learner) estimates

## Usage

```
get_SCLearner(k, q, pred.matrix, gamma.EB, V.EB)
```

## Arguments

k	number of external models
q	total number of covariates (X,B) including the intercept (i.e. $q = \text{ncol}(X) + \text{ncol}(B) + 1$ )
pred.matrix	a predictor matrix (q rows by k columns) that specifies the full model variables in the rows, and the external models on the columns. An entry of 0 means that the row variable is NOT used in the column external model; 1 represents that it is used.
gamma.EB	bind all k EB estimates in order (q rows by k columns), i.e. <code>cbind(gamma.EB1, ..., gamma.EBk)</code>
V.EB	variance-covariance matrix obtained from function <code>get_var_EB()</code>

## Value

a list with `gamma.SCLearner` and `var.SCLearner`



```

#It's important to reorder gamma.CML2 so that it follows the order (X1, X2, X3, B)
# as gamma.I and gamma.CML1
gamma.CML2 = c(gamma.CML2[1], gamma.CML2[3], gamma.CML2[2], gamma.CML2[4])

#Get Variance-covariance matrix of c(gamma.I, gamma.CML1, gamma.CML2)
asy.CML = asympVar_LogReg(k=2, p=2,q=4, YInt=data.n$Y, XInt=data.n[,c('X1','X2')],
                          BInt=data.n$B, gammaHatInt=gamma.I, betaHatExt_list=betaHatExt_list,
                          CovExt_list=CovExt_list, rho=rho, ExUncertainty=TRUE)

#Get the empirical Bayes (EB) estimates
gamma.EB1 = get_gamma_EB(gamma.I, gamma.CML1, asy.CML[["asyV.I"]][["gamma.EB"]])
gamma.EB2 = get_gamma_EB(gamma.I, gamma.CML2, asy.CML[["asyV.I"]][["gamma.EB"]])

#Get the asymptotic variance of the EB estimates
V.EB = get_var_EB(k=2, q=4, gamma.CML=c(gamma.CML1, gamma.CML2),
                  gamma.I = gamma.I, asy.CML=asy.CML, seed=2333, nsim=2000)

#Get the SC-Learner estimates and the corresponding variance-covariance matrix
pred.matrix = matrix(c(1,1,1,0,
                       1,1,0,0), 4, 2)
rownames(pred.matrix) = c('int','X1','X2','B')
colnames(pred.matrix) = c('E1','E2')

get_SCLearner(k=2,
              q=4,
              pred.matrix=pred.matrix,
              gamma.EB=cbind(gamma.EB1, gamma.EB2),
              V.EB)

```

---

get_var_EB	<i>Using simulation to obtain the asymptotic variance-covariance matrix of gamma_EB, package corpcor and MASS are required</i>
------------	--------------------------------------------------------------------------------------------------------------------------------

---

### Description

Using simulation to obtain the asymptotic variance-covariance matrix of gamma\_EB, package corpcor and MASS are required

### Usage

```
get_var_EB(k, q, gamma.CML, gamma.I, asy.CML, seed = 2333, nsim = 2000)
```

### Arguments

k	number of external models
q	total number of covariates (X,B) including the intercept (i.e. $q = \text{ncol}(X) + \text{ncol}(B) + 1$ )
gamma.CML	stack all k CML estimates in order, i.e. $c(\text{gamma.CML1}, \dots, \text{gamma.CMLk})$

gamma.I	direct regression estimates using the internal data only
asy.CML	a list of the estimated asymptotic variance-covariance matrix of $c(\text{gamma\_CML}, \text{gamma\_I})$ from the output of function <code>asymptVar_LinReg()</code> or <code>asymptVar_LogReg()</code>
seed	specify seed for simulation
nsim	number of simulation, default <code>nsim=2,000</code>

### Value

a list with: `Var(gamma_EB)`, `Cov(gamma_EB, gamma_I)` and `Cov(gamma_EBi, gamma_EBj)`

### References

Gu, T., Taylor, J.M.G. and Mukherjee, B. (2020). An ensemble meta-prediction framework to integrate multiple regression models into a current study. Manuscript in preparation.

### Examples

```
# Full model: Y|X1, X2, B
# Reduced model 1: Y|X1 of sample size m1
# Reduced model 2: Y|X2 of sample size m2
# (X1, X2, B) follows normal distribution with mean zero, variance one and correlation 0.3
# Y|X1, X2, B follows Bernoulli[expit(-1-0.5*X1-0.5*X2+0.5*B)], where expit(x)=exp(x)/[1+exp(x)]
set.seed(2333)
n = 1000
data.n = data.frame(matrix(ncol = 4, nrow = n))
colnames(data.n) = c('Y', 'X1', 'X2', 'B')
data.n[,c('X1', 'X2', 'B')] = MASS::mvrnorm(n, rep(0,3), diag(0.7,3)+0.3)
data.n$Y = rbinom(n, 1, expit(-1 - 0.5*data.n$X1 - 0.5*data.n$X2 + 0.5*data.n$B))

# Generate the beta estimates from the external reduced model:
# generate a data of size m from the full model first, then fit the reduced regression
# to obtain the beta estimates and the corresponding estimated variance
m = m1 = m2 = 30000
data.m = data.frame(matrix(ncol = 4, nrow = m))
names(data.m) = c('Y', 'X1', 'X2', 'B')
data.m[,c('X1', 'X2', 'B')] = MASS::mvrnorm(m, rep(0,3), diag(0.7,3)+0.3)
data.m$Y = rbinom(m, 1, expit(-1 - 0.5*data.m$X1 - 0.5*data.m$X2 + 0.5*data.m$B))

#fit Y|X to obtain the external beta estimates, save the beta estimates and
# the corresponding estimated variance
fit.E1 = glm(Y ~ X1, data = data.m, family = binomial(link='logit'))
fit.E2 = glm(Y ~ X2, data = data.m, family = binomial(link='logit'))
beta.E1 = coef(fit.E1)
beta.E2 = coef(fit.E2)
names(beta.E1) = c('int', 'X1')
names(beta.E2) = c('int', 'X2')
V.E1 = vcov(fit.E1)
V.E2 = vcov(fit.E2)

#Save all the external model information into lists for later use
betaHatExt_list = list(Ext1 = beta.E1, Ext2 = beta.E2)
```

```

CovExt_list = list(Ext1 = V.E1, Ext2 = V.E2)
rho = list(Ext1 = n/m1, Ext2 = n/m2)

#get full model estimate from direct regression using the internal data only
fit.gamma.I = glm(Y ~ X1 + X2 + B, data = data.n, family = binomial(link='logit'))
gamma.I = coef(fit.gamma.I)

#Get CML estimates using internal data and the beta estimates from the external
# model 1 and 2, respectively
gamma.CML1 = fxnCC_LogReg(p=2, q=4, YInt=data.n$Y, XInt=data.n$X1,
  Bint=cbind(data.n$X2, data.n$B), betaHatExt=beta.E1, gammaHatInt=gamma.I,
  n=nrow(data.n), tol=1e-8, maxIter=400, factor=1)[["gammaHat"]]
gamma.CML2 = fxnCC_LogReg(p=2, q=4, YInt=data.n$Y, XInt=data.n$X2,
  Bint=cbind(data.n$X1, data.n$B), betaHatExt=beta.E2, gammaHatInt=gamma.I,
  n=nrow(data.n), tol=1e-8, maxIter=400, factor=1)[["gammaHat"]]
#It's important to reorder gamma.CML2 so that it follows the order (X1, X2, X3, B)
# as gamma.I and gamma.CML1
gamma.CML2 = c(gamma.CML2[1], gamma.CML2[3], gamma.CML2[2], gamma.CML2[4])

#Get Variance-covariance matrix of c(gamma.I, gamma.CML1, gamma.CML2)
asy.CML = asympVar_LogReg(k=2, p=2, q=4, YInt=data.n$Y, XInt=data.n[c('X1', 'X2')],
  Bint=data.n$B, gammaHatInt=gamma.I, betaHatExt_list=betaHatExt_list,
  CovExt_list=CovExt_list, rho=rho, ExUncertainty=TRUE)

#Get the empirical Bayes (EB) estimates
gamma.EB1 = get_gamma_EB(gamma.I, gamma.CML1, asy.CML[["asyV.I"]])[["gamma.EB"]]
gamma.EB2 = get_gamma_EB(gamma.I, gamma.CML2, asy.CML[["asyV.I"]])[["gamma.EB"]]

#Get the asymptotic variance of the EB estimates
V.EB = get_var_EB(k=2,
  q=4,
  gamma.CML=c(gamma.CML1, gamma.CML2),
  gamma.I = gamma.I,
  asy.CML=asy.CML,
  seed=2333,
  nsim=2000)
asyV.EB1 = V.EB[['asyV.EB']][[1]] #variance of gamma.EB1
asyV.EB2 = V.EB[['asyV.EB']][[2]] #variance of gamma.EB2
asyCov.EB1.I = V.EB[['asyCov.EB.I']][[1]] #covariance of gamma.EB1 and gamma.I
asyCov.EB2.I = V.EB[['asyCov.EB.I']][[2]] #covariance of gamma.EB2 and gamma.I
asyCov.EB12 = V.EB[['asyCov.EB']][[12]] #covariance of gamma.EB1 and gamma.EB2

```

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