

# latex-math Macros

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Latex macros like `\frac{#1}{#2}` with arguments are displayed as  $\frac{\#1}{\#2}$ .

Note that macro declarations may only span a single line to be displayed correctly in the below tables.

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## basic-math

Macro	Notation	Comment
<code>\N</code>	$\mathbb{N}$	N, naturals
<code>\Z</code>	$\mathbb{Z}$	Z, integers
<code>\Q</code>	$\mathbb{Q}$	Q, rationals
<code>\R</code>	$\mathbb{R}$	R, reals
<code>\C</code>	$\mathbb{C}$	C, complex
<code>\continuous</code>	$\mathcal{C}$	C, space of continuous functions
<code>\M</code>	$\mathcal{M}$	machine numbers
<code>\epsm</code>	$\epsilon_m$	maximum error
<code>\setzo</code>	$\{0, 1\}$	set 0, 1
<code>\setmp</code>	$\{-1, +1\}$	set -1, 1
<code>\unitint</code>	$[0, 1]$	unit interval
<code>\xt</code>	$\tilde{x}$	x tilde
<code>\argmin</code>	arg min	argmin
<code>\argmax</code>	arg max	argmax
<code>\argminlim</code>	arg min	argmin with limits
<code>\argmaxlim</code>	arg max	argmax with limits
<code>\sign</code>	sign	sign, signum
<code>\I</code>	$\mathbb{I}$	I, indicator
<code>\order</code>	$\mathcal{O}$	O, order
<code>\bigO</code>	$\mathcal{O}$	Big-O Landau
<code>\littleo</code>	$o$	Little-o Landau
<code>\pd</code>	$\frac{\partial \#1}{\partial \#2}$	partial derivative
<code>\floorlr</code>	$\lfloor \#1 \rfloor$	floor
<code>\ceillr</code>	$\lceil \#1 \rceil$	ceiling
<code>\indep</code>	$\perp\!\!\!\perp$	independence symbol
<code>\sumin</code>	$\sum_{i=1}^n$	summation from i=1 to n
<code>\sumim</code>	$\sum_{i=1}^m$	summation from i=1 to m
<code>\sumjn</code>	$\sum_{j=1}^n$	summation from j=1 to p
<code>\sumjp</code>	$\sum_{j=1}^p$	summation from j=1 to p
<code>\sumik</code>	$\sum_{i=1}^k$	summation from i=1 to k
<code>\sumkg</code>	$\sum_{k=1}^g$	summation from k=1 to g
<code>\sumjg</code>	$\sum_{j=1}^g$	summation from j=1 to g
<code>\summM</code>	$\sum_{m=1}^M$	summation from m=1 to M

<code>\meanin</code>	$\frac{1}{n} \sum_{i=1}^n$	mean from i=1 to n
<code>\meanim</code>	$\frac{1}{m} \sum_{i=1}^m$	mean from i=1 to n
<code>\meankg</code>	$\frac{1}{g} \sum_{k=1}^g$	mean from k=1 to g
<code>\meanmM</code>	$\frac{1}{M} \sum_{m=1}^M$	mean from m=1 to M
<code>\prodin</code>	$\prod_{i=1}^n$	product from i=1 to n
<code>\prodkg</code>	$\prod_{k=1}^g$	product from k=1 to g
<code>\prodj p</code>	$\prod_{j=1}^p$	product from j=1 to p
<code>\one</code>	<b>1</b>	1, unitvector
<code>\zero</code>	<b>0</b>	0-vector
<code>\id</code>	<b>I</b>	I, identity
<code>\diag</code>	diag	diag, diagonal
<code>\trace</code>	tr	tr, trace
<code>\spn</code>	span	span
<code>\scp</code>	$\langle \#1, \#2 \rangle$	<.,.>, scalarproduct
<code>\mat</code>	$(\#1)$	short pmatrix command
<code>\Amat</code>	<b>A</b>	matrix A
<code>\Deltab</code>	<b><math>\Delta</math></b>	error term for vectors
<code>\P</code>	P	P, probability
<code>\E</code>	E	E, expectation
<code>\var</code>	Var	Var, variance
<code>\cov</code>	Cov	Cov, covariance
<code>\corr</code>	Corr	Corr, correlation
<code>\normal</code>	$\mathcal{N}$	N of the normal distribution
<code>\iid</code>	$\overset{i.i.d}{\sim}$	dist with i.i.d superscript
<code>\distas</code>	$\overset{\#1}{\sim}$	... is distributed as ...

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## basic-ml

Macro	Notation	Comment
\Xspace	$\mathcal{X}$	X, input space
\Yspace	$\mathcal{Y}$	Y, output space
\Zspace	$\mathcal{Z}$	Z, space of sampled datapoints
\nset	$\{1, \dots, n\}$	set from 1 to n
\pset	$\{1, \dots, p\}$	set from 1 to p
\gset	$\{1, \dots, g\}$	set from 1 to g
\Pxy	$\mathbb{P}_{xy}$	$P_{xy}$
\Exy	$\mathbb{E}_{xy}$	$E_{xy}$ : Expectation over random variables xy
\xv	$\mathbf{x}$	vector x (bold)
\xtil	$\tilde{\mathbf{x}}$	vector x-tilde (bold)
\yv	$\mathbf{y}$	vector y (bold)
\xy	$(\mathbf{x}, y)$	observation (x, y)
\xvec	$(x_1, \dots, x_p)^\top$	(x1, ..., xp)
\Xmat	$\mathbf{X}$	Design matrix
\allDatasets	$\mathcal{D}$	The set of all datasets
\allDatasetsn	$\mathcal{D}_n$	The set of all datasets of size n
\D	$\mathcal{D}$	D, data
\Dn	$\mathcal{D}_n$	D_n, data of size n
\Dtrain	$\mathcal{D}_{\text{train}}$	D_train, training set
\Dtest	$\mathcal{D}_{\text{test}}$	D_test, test set
\xyi	$(\mathbf{x}^{(\#1)}, y^{(\#1)})$	(x~i, y~i), i-th observation
\Dset	$((\mathbf{x}^{(1)}, y^{(1)}), \dots, (\mathbf{x}^{(n)}, y^{(n)}))$	{(x1,y1), ..., (xn,yn)}, data
\defAllDatasetsn	$(\mathcal{X} \times \mathcal{Y})^n$	Def. of the set of all datasets of size n
\defAllDatasets	$\bigcup_{n \in \mathbb{N}} (\mathcal{X} \times \mathcal{Y})^n$	Def. of the set of all datasets
\xdat	$\{\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(n)}\}$	{x1, ..., xn}, input data
\ydat	$\{\mathbf{y}^{(1)}, \dots, \mathbf{y}^{(n)}\}$	{y1, ..., yn}, input data
\yvec	$(y^{(1)}, \dots, y^{(n)})^\top$	(y1, ..., yn), vector of outcomes
\greekxi	$\mathbf{x}^{(i)}$	Greek letter xi
\xi	$\mathbf{x}^{(\#1)}$	x~i, i-th observed value of x
\yi	$y^{(\#1)}$	y~i, i-th observed value of y
\xivec	$(x_1^{(i)}, \dots, x_p^{(i)})^\top$	(x1~i, ..., xp~i), i-th observation vector
\xj	$\mathbf{x}_j$	x_j, j-th feature
\xjvec	$(x_j^{(1)}, \dots, x_j^{(n)})^\top$	(x1_j, ..., xn_j), j-th feature vector
\phiv	$\phi$	Basis transformation function phi
\phixi	$\phi^{(i)}$	Basis transformation of xi: phi~i := phi(xi)
\lamv	$\boldsymbol{\lambda}$	lambda vector, hyperconfiguration vector
\Lam	$\Lambda$	Lambda, space of all hpos
\preimageInducer	$(\bigcup_{n \in \mathbb{N}} (\mathcal{X} \times \mathcal{Y})^n) \times \Lambda$	Set of all datasets times the hyperparameter space
\preimageInducerShort	$\mathcal{D} \times \Lambda$	Set of all datasets times the hyperparameter space
\ind	$\mathcal{I}$	Inducer, inducing algorithm, learning algorithm

<code>\ftrue</code>	$f_{\text{true}}$	True underlying function (if a statistical model is assumed)
<code>\ftruex</code>	$f_{\text{true}}(\mathbf{x})$	True underlying function (if a statistical model is assumed)
<code>\fx</code>	$f(\mathbf{x})$	$f(\mathbf{x})$ , continuous prediction function
<code>\fdomains</code>	$f : \mathcal{X} \rightarrow \mathbb{R}^g$	f with domain and co-domain
<code>\Hspace</code>	$\mathcal{H}$	hypothesis space where f is from
<code>\fbayes</code>	$f^*$	Bayes-optimal model
<code>\fxbayes</code>	$f^*(\mathbf{x})$	Bayes-optimal model
<code>\fkx</code>	$f_{\#1}(\mathbf{x})$	$f_{\#j}(\mathbf{x})$ , discriminant component function
<code>\fh</code>	$\hat{f}$	f hat, estimated prediction function
<code>\fxh</code>	$\hat{f}(\mathbf{x})$	fhat(x)
<code>\fxt</code>	$f(\mathbf{x} \mid \boldsymbol{\theta})$	$f(\mathbf{x} \mid \text{theta})$
<code>\fxi</code>	$f(\mathbf{x}^{(i)})$	$f(\mathbf{x}^{\wedge(i)})$
<code>\fxih</code>	$\hat{f}(\mathbf{x}^{(i)})$	$f(\mathbf{x}^{\wedge(i)})$
<code>\fxit</code>	$f(\mathbf{x}^{(i)} \mid \boldsymbol{\theta})$	$f(\mathbf{x}^{\wedge(i)} \mid \text{theta})$
<code>\fhD</code>	$\hat{f}_{\mathcal{D}}$	fhat_D, estimate of f based on D
<code>\fhDtrain</code>	$\hat{f}_{\mathcal{D}_{\text{train}}}$	fhat_Dtrain, estimate of f based on D
<code>\fhDnlam</code>	$\hat{f}_{\mathcal{D}, \lambda}$	model learned on Dn with hp lambda
<code>\fhDlam</code>	$\hat{f}_{\mathcal{D}, \lambda}$	model learned on D with hp lambda
<code>\fhDnlams</code>	$\hat{f}_{\mathcal{D}, \lambda^*}$	model learned on Dn with optimal hp lambda
<code>\fhDlams</code>	$\hat{f}_{\mathcal{D}, \lambda^*}$	model learned on D with optimal hp lambda
<code>\hx</code>	$h(\mathbf{x})$	$h(\mathbf{x})$ , discrete prediction function
<code>\hh</code>	$\hat{h}$	h hat
<code>\hxx</code>	$\hat{h}(\mathbf{x})$	hhat(x)
<code>\hxt</code>	$h(\mathbf{x} \mid \boldsymbol{\theta})$	$h(\mathbf{x} \mid \text{theta})$
<code>\hxi</code>	$h(\mathbf{x}^{(i)})$	$h(\mathbf{x}^{\wedge(i)})$
<code>\hxit</code>	$h(\mathbf{x}^{(i)} \mid \boldsymbol{\theta})$	$h(\mathbf{x}^{\wedge(i)} \mid \text{theta})$
<code>\hbayes</code>	$h^*$	Bayes-optimal classification model
<code>\hxbayes</code>	$h^*(\mathbf{x})$	Bayes-optimal classification model
<code>\yh</code>	$\hat{y}$	yhat for prediction of target
<code>\yih</code>	$\hat{y}^{(i)}$	yhat^(i) for prediction of ith targiet
<code>\resi</code>	$y^{(i)} - \hat{y}^{(i)}$	
<code>\thetah</code>	$\hat{\boldsymbol{\theta}}$	theta hat
<code>\thetav</code>	$\boldsymbol{\theta}$	theta vector
<code>\thetavh</code>	$\hat{\boldsymbol{\theta}}$	theta vector hat
<code>\thetat</code>	$\boldsymbol{\theta}^{[\#1]}$	theta^[t] in optimization
<code>\thetatn</code>	$\boldsymbol{\theta}^{[\#1+1]}$	theta^[t+1] in optimization
<code>\thetahDnlam</code>	$\hat{\boldsymbol{\theta}}_{\mathcal{D}_n, \lambda}$	theta learned on Dn with hp lambda
<code>\thetahDlam</code>	$\hat{\boldsymbol{\theta}}_{\mathcal{D}, \lambda}$	theta learned on D with hp lambda
<code>\mint</code>	$\min_{\boldsymbol{\theta} \in \Theta}$	min problem theta
<code>\argmint</code>	$\arg \min_{\boldsymbol{\theta} \in \Theta}$	argmin theta
<code>\pdf</code>	$p$	p
<code>\pdfx</code>	$p(\mathbf{x})$	p(x)
<code>\pixt</code>	$\pi(\mathbf{x} \mid \boldsymbol{\theta})$	pi(x theta), pdf of x given theta
<code>\pixit</code>	$\pi(\mathbf{x}^{(\#1)} \mid \boldsymbol{\theta})$	pi(x^i theta), pdf of x given theta

<code>\pixii</code>	$\pi(\mathbf{x}^{(\#1)})$	$\text{pi}(\mathbf{x}^{\wedge i})$ , pdf of i-th x
<code>\pdfxy</code>	$p(\mathbf{x}, y)$	$p(\mathbf{x}, y)$
<code>\pdfxyt</code>	$p(\mathbf{x}, y \mid \boldsymbol{\theta})$	$p(\mathbf{x}, y \mid \text{theta})$
<code>\pdfxyit</code>	$p(\mathbf{x}^{(i)}, y^{(i)} \mid \boldsymbol{\theta})$	$p(\mathbf{x}^{\wedge(i)}, y^{\wedge(i)} \mid \text{theta})$
<code>\pdfxyk</code>	$p(\mathbf{x} \mid y = \#1)$	$p(\mathbf{x} \mid y = k)$
<code>\lpdfxyk</code>	$\log p(\mathbf{x} \mid y = \#1)$	$\log p(\mathbf{x} \mid y = k)$
<code>\pdfxyik</code>	$p(\mathbf{x}^{(i)} \mid y = \#1)$	$p(\mathbf{x}^{\wedge i} \mid y = k)$
<code>\pik</code>	$\pi_{\#1}$	$\text{pi\_k}$ , prior
<code>\pih</code>	$\hat{\pi}$	$\text{pi hat}$ , estimated prior (binary classification)
<code>\pikh</code>	$\hat{\pi}_{\#1}$	$\text{pi\_k hat}$ , estimated prior
<code>\lpik</code>	$\log \pi_{\#1}$	$\log \text{pi\_k}$ , log of the prior
<code>\pit</code>	$\pi(\boldsymbol{\theta})$	Prior probability of parameter theta
<code>\post</code>	$\mathbb{P}(y = 1 \mid \mathbf{x})$	$P(y = 1 \mid \mathbf{x})$ , post. prob for y=1
<code>\postk</code>	$\mathbb{P}(y = \#1 \mid \mathbf{x})$	$P(y = k \mid y)$ , post. prob for y=k
<code>\pidomains</code>	$\pi : \mathcal{X} \rightarrow [0, 1]$	pi with domain and co-domain
<code>\pibayes</code>	$\pi^*$	Bayes-optimal classification model
<code>\pixbayes</code>	$\pi^*(\mathbf{x})$	Bayes-optimal classification model
<code>\piastxtil</code>	$\pi^*(\tilde{\mathbf{x}})$	Bayes-optimal classification model
<code>\pix</code>	$\pi(\mathbf{x})$	$\text{pi}(\mathbf{x})$ , $P(y = 1 \mid \mathbf{x})$
<code>\piv</code>	$\boldsymbol{\pi}$	pi, bold, as vector
<code>\pikx</code>	$\pi_{\#1}(\mathbf{x})$	$\text{pi\_k}(\mathbf{x})$ , $P(y = k \mid \mathbf{x})$
<code>\pikxt</code>	$\pi_{\#1}(\mathbf{x} \mid \boldsymbol{\theta})$	$\text{pi\_k}(\mathbf{x} \mid \text{theta})$ , $P(y = k \mid \mathbf{x}, \text{theta})$
<code>\pixh</code>	$\hat{\pi}(\mathbf{x})$	$\text{pi}(\mathbf{x}) \text{ hat}$ , $P(y = 1 \mid \mathbf{x}) \text{ hat}$
<code>\pikxh</code>	$\hat{\pi}_{\#1}(\mathbf{x})$	$\text{pi\_k}(\mathbf{x}) \text{ hat}$ , $P(y = k \mid \mathbf{x}) \text{ hat}$
<code>\pixih</code>	$\hat{\pi}(\mathbf{x}^{(i)})$	$\text{pi}(\mathbf{x}^{\wedge(i)})$ with hat
<code>\pikxih</code>	$\hat{\pi}_{\#1}(\mathbf{x}^{(i)})$	$\text{pi\_k}(\mathbf{x}^{\wedge(i)})$ with hat
<code>\pdfyigxt</code>	$p(y \mid \mathbf{x}, \boldsymbol{\theta})$	$p(y \mid \mathbf{x}, \text{theta})$
<code>\pdfyigxit</code>	$p(y^{(i)} \mid \mathbf{x}^{(i)}, \boldsymbol{\theta})$	$p(y^{\wedge i} \mid \mathbf{x}^{\wedge i}, \text{theta})$
<code>\lpdfyigxt</code>	$\log p(y \mid \mathbf{x}, \boldsymbol{\theta})$	$\log p(y \mid \mathbf{x}, \text{theta})$
<code>\lpdfyigxit</code>	$\log p(y^{(i)} \mid \mathbf{x}^{(i)}, \boldsymbol{\theta})$	$\log p(y^{\wedge i} \mid \mathbf{x}^{\wedge i}, \text{theta})$
<code>\bayesrulek</code>	$\frac{\mathbb{P}(\mathbf{x} \mid y = \#1) \mathbb{P}(y = \#1)}{\mathbb{P}(\mathbf{x})}$	Bayes rule
<code>\muv</code>	$\boldsymbol{\mu}$	expectation vector of Gaussian
<code>\muk</code>	$\boldsymbol{\mu}_{\#1}$	mean vector of class-k Gaussian (discr analysis)
<code>\mukh</code>	$\hat{\boldsymbol{\mu}}_{\#1}$	estimated mean vector of class-k Gaussian (discr analysis)
<code>\rx</code>	$r(\mathbf{x})$	residual
<code>\eps</code>	$\epsilon$	residual, stochastic
<code>\epsv</code>	$\boldsymbol{\epsilon}$	residual, stochastic, as vector
<code>\epsi</code>	$\epsilon^{(i)}$	$\text{epsilon}^{\wedge i}$ , residual, stochastic
<code>\epsh</code>	$\hat{\epsilon}$	residual, estimated
<code>\epsvh</code>	$\hat{\boldsymbol{\epsilon}}$	residual, estimated, vector
<code>\yf</code>	$y f(\mathbf{x})$	y f(x), margin
<code>\yfi</code>	$y^{(i)} f(\mathbf{x}^{(i)})$	$y^{\wedge i} f(\mathbf{x}^{\wedge i})$ , margin
<code>\Sigmah</code>	$\hat{\Sigma}$	estimated covariance matrix
<code>\Sigmahj</code>	$\hat{\Sigma}_j$	estimated covariance matrix for the j-th class
<code>\Lyf</code>	$L(y, f)$	$L(y, f)$ , loss function

\Lypi	$L(y, \pi)$	$L(y, \pi)$ , loss function
\Lxy	$L(y, f(\mathbf{x}))$	$L(y, f(\mathbf{x}))$ , loss function
\Lxyi	$L(y^{(i)}, f(\mathbf{x}^{(i)}))$	loss of observation
\Lxyt	$L(y, f(\mathbf{x}   \boldsymbol{\theta}))$	loss with f parameterized
\Lxyit	$L(y^{(i)}, f(\mathbf{x}^{(i)}   \boldsymbol{\theta}))$	loss of observation with f parameterized
\Lxym	$L(y^{(i)}, f(\tilde{\mathbf{x}}^{(i)}   \boldsymbol{\theta}))$	loss of observation with f parameterized
\Lpixy	$L(y, \pi(\mathbf{x}))$	loss in classification
\Lpiy	$L(y, \pi)$	loss in classification
\Lpiv	$L(y, \boldsymbol{\pi})$	loss in classification
\Lpixyi	$L(y^{(i)}, \pi(\mathbf{x}^{(i)}))$	loss of observation in classification
\Lpixyt	$L(y, \pi(\mathbf{x}   \boldsymbol{\theta}))$	loss with pi parameterized
\Lpixyit	$L(y^{(i)}, \pi(\mathbf{x}^{(i)}   \boldsymbol{\theta}))$	loss of observation with pi parameterized
\Lhy	$L(y, h)$	$L(y, h)$ , loss function on discrete classes
\Lhxy	$L(y, h(\mathbf{x}))$	$L(y, h(\mathbf{x}))$ , loss function on discrete classes
\Lr	$L(r)$	$L(r)$ , loss defined on residual (reg) / margin (classif)
\lone	$ y - f(\mathbf{x}) $	L1 loss
\ltwo	$(y - f(\mathbf{x}))^2$	L2 loss
\lbernoullimp	$\ln(1 + \exp(-y \cdot f(\mathbf{x})))$	Bernoulli loss for -1, +1 encoding
\lbernoullizo	$-y \cdot f(\mathbf{x}) + \log(1 + \exp(f(\mathbf{x})))$	Bernoulli loss for 0, 1 encoding
\lcrossent	$-y \log(\pi(\mathbf{x})) - (1 - y) \log(1 - \pi(\mathbf{x}))$	cross-entropy loss
\lbrier	$(\pi(\mathbf{x}) - y)^2$	Brier score
\risk	$\mathcal{R}$	R, risk
\riskbayes	$\mathcal{R}^*$	
\riskf	$\mathcal{R}(f)$	$\mathcal{R}(f)$ , risk
\riskdef	$\mathbb{E}_{y \mathbf{x}}(L(y, f(\mathbf{x})))$	risk def (expected loss)
\riskt	$\mathcal{R}(\boldsymbol{\theta})$	$\mathcal{R}(\theta)$ , risk
\riske	$\mathcal{R}_{\text{emp}}$	$\mathcal{R}_{\text{emp}}$ , empirical risk w/o factor 1 / n
\riskeb	$\bar{\mathcal{R}}_{\text{emp}}$	$\mathcal{R}_{\text{emp}}$ , empirical risk w/ factor 1 / n
\riskef	$\mathcal{R}_{\text{emp}}(f)$	$\mathcal{R}_{\text{emp}}(f)$
\risket	$\mathcal{R}_{\text{emp}}(\boldsymbol{\theta})$	$\mathcal{R}_{\text{emp}}(\theta)$
\riskr	$\mathcal{R}_{\text{reg}}$	$\mathcal{R}_{\text{reg}}$ , regularized risk
\riskrt	$\mathcal{R}_{\text{reg}}(\boldsymbol{\theta})$	$\mathcal{R}_{\text{reg}}(\theta)$
\riskrf	$\mathcal{R}_{\text{reg}}(f)$	$\mathcal{R}_{\text{reg}}(f)$
\riskrth	$\hat{\mathcal{R}}_{\text{reg}}(\boldsymbol{\theta})$	hat $\mathcal{R}_{\text{reg}}(\theta)$
\risketh	$\hat{\mathcal{R}}_{\text{emp}}(\boldsymbol{\theta})$	hat $\mathcal{R}_{\text{emp}}(\theta)$
\LL	$\mathcal{L}$	L, likelihood
\LLt	$\mathcal{L}(\boldsymbol{\theta})$	$\mathcal{L}(\theta)$ , likelihood
\LLtx	$\mathcal{L}(\boldsymbol{\theta} \mathbf{x})$	$\mathcal{L}(\theta \mathbf{x})$ , likelihood
\logl	$\ell$	l, log-likelihood
\loglt	$\ell(\boldsymbol{\theta})$	$\ell(\theta)$ , log-likelihood
\logltx	$\ell(\boldsymbol{\theta} \mathbf{x})$	$\ell(\theta \mathbf{x})$ , log-likelihood
\errtrain	$\text{err}_{\text{train}}$	training error
\errtest	$\text{err}_{\text{test}}$	test error
\errexp	$\overline{\text{err}_{\text{test}}}$	avg training error
\thx	$\boldsymbol{\theta}^\top \mathbf{x}$	linear model



`\olsest`

$$(\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{y}$$

OLS estimator in LM

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## ml-ensembles

Macro	Notation	Comment
\bl	$b^{[\#1]}$	baselearner, default m
\blh	$\hat{b}^{[\#1]}$	estimated base learner, default m
\blx	$b^{[\#1]}(\mathbf{x})$	baselearner, default m
\blf	$f^{[\#1]}$	baselearner: scores, default m
\blfh	$\hat{f}^{[\#1]}$	estimated baselearner: scores, default m
\blfhx	$\hat{f}^{[\#1]}(\mathbf{x})$	estimated baselearner: scores of x, default m
\bll	$h^{[\#1]}$	baselearner: hard labels, default m
\bllh	$\hat{h}^{[\#1]}$	estimated baselearner: hard labels, default m
\bllhx	$\hat{h}^{[\#1]}(\mathbf{x})$	estimated baselearner: hard labels of x, default m
\blp	$\pi^{[\#1]}$	baselearner: probabilities, default m
\blph	$\hat{\pi}^{[\#1]}$	estimated baselearner: probabilities, default m
\blphxk	$\hat{\pi}_k^{[\#1]}(\mathbf{x})$	estimated baselearner: probabilities of x for class k, default m
\fM	$f^{[M]}(\mathbf{x})$	ensembled predictor
\fMh	$\hat{f}^{[M]}(\mathbf{x})$	estimated ensembled predictor
\ambifM	$\Delta(f^{[M]}(\mathbf{x}))$	ambiguity/instability of ensemble
\betam	$\beta^{[\#1]}$	weight of basemodel m
\betamh	$\hat{\beta}^{[\#1]}$	weight of basemodel m with hat
\betaM	$\beta^{[M]}$	last baselearner
\ib	IB	In-Bag (IB)
\ibm	$IB^{[m]}$	In-Bag (IB) for m-th bootstrap
\oob	OOB	Out-of-Bag (OOB)
\oobm	$OOB^{[m]}$	Out-of-Bag (OOB) for m-th bootstrap
\fm	$f^{[\#1]}$	prediction in iteration m
\fmh	$\hat{f}^{[\#1]}$	prediction in iteration m
\fmd	$f^{[\#1-1]}$	prediction m-1
\fmdh	$\hat{f}^{[\#1-1]}$	prediction m-1
\errm	$err^{[\#1]}$	weighted in-sample misclassification rate
\wm	$w^{[\#1]}$	weight vector of basemodel m
\wmi	$w^{[\#1](i)}$	weight of obs i of basemodel m
\thetam	$\theta^{[\#1]}$	parameters of basemodel m
\thetamh	$\hat{\theta}^{[\#1]}$	parameters of basemodel m with hat
\blxt	$b(\mathbf{x}, \theta^{[\#1]})$	baselearner, default m
\ens	$\sum_{m=1}^M \beta^{[m]} b(\mathbf{x}, \theta^{[m]})$	ensemble
\rmm	$\hat{r}^{[\#1]}$	pseudo residuals
\rmi	$\hat{r}^{[\#1](i)}$	pseudo residuals
\Rtm	$R_t^{[\#1]}$	terminal-region
\Tm	$T^{[\#1]}$	terminal-region
\ctm	$c_t^{[\#1]}$	mean, terminal-regions
\ctmh	$\hat{c}_t^{[\#1]}$	mean, terminal-regions with hat
\ctmt	$\hat{\tilde{c}}_t^{[\#1]}$	mean, terminal-regions

<code>\Lp</code>	$L'$	
<code>\Ldp</code>	$L''$	
<code>\Lpleft</code>	$L'_{\text{left}}$	
<code>\ts</code>	$\boldsymbol{\theta}^*$	theta*
<code>\bljt</code>	$b^{[j]}(\mathbf{x}, \boldsymbol{\theta})$	BL j with theta
<code>\bljts</code>	$b^{[j]}(\mathbf{x}, \boldsymbol{\theta}^*)$	BL j with theta*

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## ml-eval

Macro	Notation	Comment
<code>\ntest</code>	$n_{\text{test}}$	size of the test set
<code>\ntrain</code>	$n_{\text{train}}$	size of the train set
<code>\ntesti</code>	$n_{\text{test},\#1}$	size of the i-th test set
<code>\ntraini</code>	$n_{\text{train},\#1}$	size of the i-th train set
<code>\Jtrain</code>	$J_{\text{train}}$	index vector train data
<code>\Jtest</code>	$J_{\text{test}}$	index vector test data
<code>\Jtraini</code>	$J_{\text{train},\#1}$	index vector i-th train dataset
<code>\Jtesti</code>	$J_{\text{test},\#1}$	index vector i-th test dataset
<code>\Dtraini</code>	$\mathcal{D}_{\text{train},\#1}$	$\mathcal{D}_{\text{train},i}$ , i-th training set
<code>\Dtesti</code>	$\mathcal{D}_{\text{test},\#1}$	$\mathcal{D}_{\text{test},i}$ , i-th test set
<code>\JSpace</code>	$\{1, \dots, n\}^{\#1}$	space of train indices of size $n_{\text{train}}$
<code>\JtrainSpace</code>	$\{1, \dots, n\}^{n_{\text{train}}}$	space of train indices of size $n_{\text{train}}$
<code>\JtestSpace</code>	$\{1, \dots, n\}^{n_{\text{test}}}$	space of train indices of size $n_{\text{test}}$
<code>\yJ</code>	$\mathbf{y}_{\#1}$	output vector associated to index J
<code>\yJDef</code>	$\left(y^{(J^{(1)})}, \dots, y^{(J^{(m)})}\right)$	def of the output vector associated to index J
<code>\JJ</code>	$\mathcal{J}$	cali-J, set of all splits
<code>\JJset</code>	$((J_{\text{train},1}, J_{\text{test},1}), \dots, (J_{\text{train},B}, J_{\text{test},B}))$	$(J_{\text{train}_1}, J_{\text{test}_1}) \dots (J_{\text{train}_B}, J_{\text{test}_B})$
<code>\Itrainlam</code>	$\mathcal{I}(\mathcal{D}_{\text{train}}, \boldsymbol{\lambda})$	
<code>\GE</code>	$\text{GE}$	GE
<code>\GEh</code>	$\widehat{\text{GE}}$	GE-hat
<code>\GEfull</code>	$\text{GE}(\mathcal{I}, \boldsymbol{\lambda}, \#1, \rho)$	GE full
<code>\GEholdout</code>	$\widehat{\text{GE}}_{J_{\text{train}}, J_{\text{test}}}(\mathcal{I}, \boldsymbol{\lambda},  J_{\text{train}} , \rho)$	GE hat holdout
<code>\GEholdouti</code>	$\widehat{\text{GE}}_{J_{\text{train},\#1}, J_{\text{test},\#1}}(\mathcal{I}, \boldsymbol{\lambda},  J_{\text{train},\#1} , \rho)$	GE hat holdout i-th set
<code>\GEhlam</code>	$\widehat{\text{GE}}(\boldsymbol{\lambda})$	GE-hat(lam)
<code>\GEhlamsubIJrho</code>	$\widehat{\text{GE}}_{\mathcal{I}, \mathcal{J}, \rho}(\boldsymbol{\lambda})$	GE-hat_I,J,rho(lam)
<code>\GEhresa</code>	$\widehat{\text{GE}}(\mathcal{I}, \mathcal{J}, \rho, \boldsymbol{\lambda})$	GE-hat_I,J,rho(lam)
<code>\GERhoDef</code>	$\lim_{n_{\text{test}} \rightarrow \infty} \mathbb{E}_{\mathcal{D}_{\text{train}}, \mathcal{D}_{\text{test}} \sim \mathbb{P}_{xy}} [\rho(\mathbf{y}_{J_{\text{test}}}, \mathbf{F}_{J_{\text{test}}, \mathcal{I}(\mathcal{D}_{\text{train}}, \boldsymbol{\lambda})})]$	GE formal def
<code>\agr</code>	$\text{agr}$	aggregate function
<code>\GEf</code>	$\text{GE}(\hat{f})$	GE of a fitted model
<code>\GEfh</code>	$\widehat{\text{GE}}(\hat{f})$	GEh of a fitted model
<code>\GEfL</code>	$\text{GE}(\hat{f}, L)$	GE of a fitted model wrt loss L
<code>\Lyfhx</code>	$L(y, \hat{f}(\mathbf{x}))$	pointwise loss of fitted model
<code>\GEnf</code>	$GE_n(\hat{f}_{\#1})$	GE of a fitted model
<code>\GEind</code>	$GE_n(\mathcal{I}_{L,O})$	GE of inducer
<code>\GED</code>	$\text{GE}_{\mathcal{D}}$	GE indexed with data
<code>\EGEn</code>	$EGE_n$	expected GE
<code>\EDn</code>	$\mathbb{E}_{ D =n}$	expectation wrt data of size n
<code>\rhoL</code>	$\rho_L$	perf. measure derived from pointwise loss
<code>\F</code>	$\mathbf{F}$	matrix of prediction scores

<code>\Fi</code>	$\mathbf{F}^{(\#1)}$	i-th row vector of the predsore mat
<code>\FJ</code>	$\mathbf{F}_{\#1}$	predscore mat idxvec J
<code>\FJf</code>	$\mathbf{F}_{J,f}$	predscore mat idxvec J and model f
<code>\FJtestfh</code>	$\mathbf{F}_{J_{\text{test}},\hat{f}}$	predscore mat idxvec Jtest and model f hat
<code>\FJtestftrain</code>	$\mathbf{F}_{J_{\text{test}},\mathcal{I}(\mathcal{D}_{\text{train}},\boldsymbol{\lambda})}$	predscore mat idxvec Jtest and model f
<code>\FJtestftraini</code>	$\mathbf{F}_{J_{\text{test}},\#1,\mathcal{I}(\mathcal{D}_{\text{train}},\#1,\boldsymbol{\lambda})}$	predscore mat i-th idxvec Jtest and model f
<code>\FJfDef</code>	$\left(f(\mathbf{x}^{(J^{(1)})}), \dots, f(\mathbf{x}^{(J^{(m)})})\right)$	def of predsore mat idxvec J and model f
<code>\preimageRho</code>	$\bigcup_{m \in \mathbb{N}} (\mathcal{Y}^m \times \mathbb{R}^{m \times g})$	Set of all datasets times HP space
<code>\np</code>	$n_+$	no. of positive instances
<code>\nn</code>	$n_-$	no. of negative instances
<code>\rn</code>	$\pi_-$	proportion negative instances
<code>\rp</code>	$\pi_+$	proportion negative instances
<code>\tp</code>	$\#TP$	true pos
<code>\fap</code>	$\#FP$	false pos (fp taken for partial derivs)
<code>\tn</code>	$\#TN$	true neg
<code>\fan</code>	$\#FN$	false neg

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ml-feature-sel

Macro	Notation	Comment
<code>\xjNull</code>	$x_{j_0}$	
<code>\xjEins</code>	$x_{j_1}$	
<code>\xl</code>	$\mathbf{x}_l$	
<code>\pushcode</code>		

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## ml-gp

Macro	Notation	Comment
<code>\fvec</code>	$[f(\mathbf{x}^{(1)}), \dots, f(\mathbf{x}^{(n)})]$	function vector
<code>\fv</code>	$\mathbf{f}$	function vector
<code>\kv</code>	$\mathbf{k}$	cov matrix partition
<code>\kxxp</code>	$k(\mathbf{x}, \mathbf{x}')$	cov of $\mathbf{x}$ , $\mathbf{x}'$
<code>\kxij</code>	$k(\mathbf{x}^{(i)}, \mathbf{x}^{(j)})$	cov of $\mathbf{x}_i$ , $\mathbf{x}_j$
<code>\mv</code>	$\mathbf{m}$	GP mean vector
<code>\Kmat</code>	$\mathbf{K}$	GP cov matrix
<code>\gaussmk</code>	$\mathcal{N}(\mathbf{m}, \mathbf{K})$	Gaussian w/ mean vec, cov mat
<code>\gp</code>	$\mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}'))$	Gaussian Process Definition
<code>\ls</code>	$\ell$	length-scale
<code>\sqexpkernel</code>	$\exp\left(-\frac{\ \mathbf{x}-\mathbf{x}'\ ^2}{2\ell^2}\right)$	squared exponential kernel
<code>\fstarvec</code>	$[f(\mathbf{x}_*^{(1)}), \dots, f(\mathbf{x}_*^{(m)})]$	pred function vector
<code>\kstar</code>	$\mathbf{k}_*$	cov of new obs with $\mathbf{x}$
<code>\kstarstar</code>	$\mathbf{k}_{**}$	cov of new obs
<code>\Kstar</code>	$\mathbf{K}_*$	cov mat of new obs with $\mathbf{x}$
<code>\Kstarstar</code>	$\mathbf{K}_{**}$	cov mat of new obs
<code>\preddistsingle</code>	$f_* \mid \mathbf{x}_*, \mathbf{X}, \mathbf{f}$	predictive distribution for single pred
<code>\preddistdefsingl</code>	$\mathcal{N}(\mathbf{k}_*^\top \mathbf{K}^{-1} \mathbf{f}, \mathbf{k}_{**} - \mathbf{k}_*^\top \mathbf{K}^{-1} \mathbf{k}_*)$	Gaussian distribution for single pred
<code>\preddist</code>	$f_* \mid \mathbf{X}_*, \mathbf{X}, \mathbf{f}$	predictive distribution
<code>\preddistdef</code>	$\mathcal{N}(\mathbf{K}_*^\top \mathbf{K}^{-1} \mathbf{f}, \mathbf{K}_{**} - \mathbf{K}_*^\top \mathbf{K}^{-1} \mathbf{K}_*)$	Gaussian predictive distribution

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## ml-hpo

Macro	Notation	Comment
\Ilam	$\mathcal{I}_{\lambda}$	inducer with HP
\LamS	$\tilde{\Lambda}$	search space
\lami	$\lambda^{(\#1)}$	lambda i
\clam	$c(\lambda)$	c(lambda)
\clamh	$c(\hat{\lambda})$	c(lambda-hat)
\lams	$\lambda^*$	theoretical min of c
\lamh	$\hat{\lambda}$	returned lambda of HPO
\lamp	$\lambda^+$	proposed lambda
\clamp	$c(\lambda^+)$	c of proposed lambda
\archive	$\mathcal{A}$	archive
\archivet	$\mathcal{A}^{[\#1]}$	archive at time step t
\tuner	$\mathcal{T}$	tuner
\tunerfull	$\mathcal{T}_{\mathcal{I}, \tilde{\Lambda}, \rho, \mathcal{J}}$	tuner with inducer, search space, perf measure, resampling strategy
\chlam	$\hat{c}(\lambda)$	post mean of SM
\shlam	$\hat{\sigma}(\lambda)$	post sd of SM
\vhlam	$\hat{\sigma}^2(\lambda)$	post var of SM
\ulam	$u(\lambda)$	acquisition function
\lambdaopt	$\lambda^*$	minimum of the black box function Psi
\metadata	$\{(\lambda^{(i)}, \Psi^{[i]})\}$	metadata for the Gaussian process
\lamvec	$(\lambda^{[1]}, \dots, \lambda^{[m_{\text{init}}]})$	vector of different inputs
\minit	$m_{\text{init}}$	size of the initial design
\lambu	$\lambda_{\text{budget}}$	single lambda_budget component HP
\lamfid	$\lambda_{\text{fid}}$	single lambda_fidelity
\lamfidl	$\lambda_{\text{fid}}^{\text{low}}$	single lambda_fidelity lower
\lamfidu	$\lambda_{\text{fid}}^{\text{upp}}$	single lambda_fidelity upper
\etahb	$\eta_{\text{HB}}$	HB multiplier eta

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## ml-infotheory

Macro	Notation	Comment
<code>\entx</code>	$-\sum_{x \in \mathcal{X}} p(x) \cdot \log p(x)$	entropy of x
<code>\dentx</code>	$-\int_{\mathcal{X}} f(x) \cdot \log f(x) dx$	diff entropy of x
<code>\jentyx</code>	$-\sum_{x \in \mathcal{X}} p(x, y) \cdot \log p(x, y)$	joint entropy of x, y
<code>\jdentyx</code>	$-\int_{\mathcal{X}, \mathcal{Y}} f(x, y) \cdot \log f(x, y) dx dy$	joint diff entropy of x, y
<code>\centyx</code>	$-\sum_{x \in \mathcal{X}} p(x) \sum_{y \in \mathcal{Y}} p(y x) \cdot \log p(y x)$	cond entropy y x
<code>\cdentyx</code>	$-\int_{\mathcal{X}, \mathcal{Y}} f(x, y) \cdot \log f(y x) dx dy$	cond diff entropy y x
<code>\xentpq</code>	$-\sum_{x \in \mathcal{X}} p(x) \cdot \log q(x)$	cross-entropy of p, q
<code>\kldpq</code>	$D_{KL}(p  q)$	KLD between p and q
<code>\kldpqt</code>	$D_{KL}(p  q_{\theta})$	KLD divergence between p and parameterized q
<code>\explogpq</code>	$\mathbb{E}_p \left[ \log \frac{p(X)}{q(X)} \right]$	expected LLR of p, q (def KLD)
<code>\sumlogpq</code>	$\sum_{x \in \mathcal{X}} p(x) \cdot \log \frac{p(x)}{q(x)}$	expected LLR of p, q (def KLD)

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## ml-interpretable

Macro	Notation	Comment
<code>\pert</code>	$\tilde{\#1}^{\#2 \#3}$	command to express that for #1 the subset #2 was perturbed given subset #3
<code>\fj</code>	$f_j$	marginal function $f_j$ , depending on feature j
<code>\fnj</code>	$f_{-j}$	marginal function $f_{-j}$ , depending on all features but j
<code>\fS</code>	$f_S$	marginal function $f_S$ depending on feature set S
<code>\fC</code>	$f_C$	marginal function $f_C$ depending on feature set C
<code>\fhj</code>	$\hat{f}_j$	marginal function $fh_j$ , depending on feature j
<code>\fhnj</code>	$\hat{f}_{-j}$	marginal function $fh_{-j}$ , depending on all features but j
<code>\fhS</code>	$\hat{f}_S$	marginal function $fh_S$ depending on feature set S
<code>\fhC</code>	$\hat{f}_C$	marginal function $fh_C$ depending on feature set C
<code>\XSmat</code>	$\mathbf{X}_S$	Design matrix subset
<code>\XCmat</code>	$\mathbf{X}_C$	Design matrix subset
<code>\Xnj</code>	$\mathbf{X}_{-j}$	Design matrix subset $-j = \{1, \dots, j-1, j+1, \dots, p\}$
<code>\fhice</code>	$\hat{f}_{\#1, ICE}$	ICE function
<code>\Scupj</code>	$S \cup \{j\}$	coalition S but without player j
<code>\Scupk</code>	$S \cup \{k\}$	coalition S but without player k
<code>\SsubP</code>	$S \subseteq P$	coalition S subset of P
<code>\SsubPnoj</code>	$S \subseteq P \setminus \{j\}$	coalition S subset of P without player j
<code>\SsubPnojk</code>	$S \subseteq P \setminus \{j, k\}$	coalition S subset of P without player k
<code>\phiij</code>	$\hat{\phi}_j^{(i)}$	Shapley value for feature j and observation i
<code>\Gspace</code>	$\mathcal{G}$	Hypothesis space for surrogate model
<code>\neigh</code>	$\phi_{\mathbf{x}}$	Proximity measure
<code>\zv</code>	$\mathbf{z}$	Sampled datapoints for surrogate
<code>\Gower</code>	$d_G$	Gower distance

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## ml-mbo

Macro	Notation	Comment
<code>\xvsi</code>	$\mathbf{x}^{[\#1]}$	x at iteration i
<code>\ysi</code>	$y^{[\#1]}$	y at iteration i
<code>\Dt</code>	$\mathcal{D}^{[\#1]}$	archive at iteration t
<code>\Dts</code>	$\mathcal{D}^{[t]} = \{(\mathbf{x}^{[i]}, y^{[i]})\}_{i=1, \dots, t}$	archive at iteration t fully
<code>\fh</code>	$\hat{s}$	surrogate mean
<code>\sh</code>	$\hat{s}$	surrogate se
<code>\fmin</code>	$f_{\min}$	current best

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**ml-multitarget**

Macro	Notation	Comment
<code>\Tspace</code>	$\mathcal{T}$	
<code>\tv</code>	$\mathbf{t}$	
<code>\tim</code>	$\mathbf{t}_m^{(i)}$	
<code>\yim</code>	$y_m^{(i)}$	

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## ml-nn

Macro	Notation	Comment
\neurons	$z_1, \dots, z_M$	vector of neurons
\hidz	$\mathbf{z}$	vector of hidden activations
\biasb	$\mathbf{b}$	bias vector
\biasc	$c$	bias in output
\wtw	$\mathbf{w}$	weight vector (general)
\Wmat	$\mathbf{W}$	weight vector (general)
\wtu	$\mathbf{u}$	weight vector of output neuron
\Oreg	$R_{reg}(\theta X, y)$	regularized objective function
\Ounreg	$R_{emp}(\theta X, y)$	unconstrained objective function
\Pen	$\Omega(\theta)$	penalty
\Oregweight	$R_{reg}(w X, y)$	regularized objective function with weight
\Oweight	$R_{emp}(w X, y)$	unconstrained objective function with weight
\Oweighti	$R_{emp}(w_i X, y)$	unconstrained objective function with weight $w_i$
\Oweightopt	$J(w^* X, y)$	unconstrained objective function with optimal weight
\Opt	$\hat{J}(\theta X, y)$	optimal objective function
\Odropout	$J(\theta, \mu X, y)$	dropout objective function
\Loss	$L(y, f(\mathbf{x}, \boldsymbol{\theta}))$	
\Lmomentumnest	$L(y^{(i)}, f(x^{(i)}, \boldsymbol{\theta} + \varphi \boldsymbol{\nu}))$	momentum risk
\Lmomentumtilde	$L(y^{(i)}, f(x^{(i)}, \tilde{\boldsymbol{\theta}}))$	Nesterov momentum risk
\Lmomentum	$L(y^{(i)}, f(x^{(i)}, \boldsymbol{\theta}))$	
\Hess	$\mathbf{H}$	
\nub	$\boldsymbol{\nu}$	
\uauto	$L(x, g(f(x)))$	undercomplete autoencoder objective function
\dauto	$L(x, g(f(\tilde{x})))$	denoising autoencoder objective function
\deltab	$\boldsymbol{\delta}$	
\Lossdeltai	$L(y^{(i)}, f(\mathbf{x}^{(i)} + \boldsymbol{\delta} \boldsymbol{\theta}))$	
\Lossdelta	$L(y, f(\mathbf{x} + \boldsymbol{\delta} \boldsymbol{\theta}))$	

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## ml-online

Macro	Notation	Comment
<code>\Aspace</code>	$\mathcal{A}$	
<code>\norm</code>	$  \#1  _2$	
<code>\llin</code>	$L^{\text{lin}}$	
<code>\lzeroone</code>	$L^{0-1}$	
<code>\lhinge</code>	$L^{\text{hinge}}$	
<code>\lexphinge</code>	$\widetilde{L^{\text{hinge}}}$	
<code>\lconv</code>	$L^{\text{conv}}$	
<code>\FTL</code>	FTL	
<code>\FTRL</code>	FTRL	
<code>\OGD</code>	OGD	
<code>\EWA</code>	EWA	
<code>\REWA</code>	REWA	
<code>\EXPthree</code>	EXP3	
<code>\EXPthreep</code>	EXP3P	
<code>\reg</code>	$\psi$	
<code>\Algo</code>	Algo	

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**ml-regu**

Macro	Notation	Comment
<code>\thetas</code>	$\boldsymbol{\theta}^*$	theta star
<code>\thetaridge</code>	$\boldsymbol{\theta}_{\text{ridge}}$	theta (RIDGE)
<code>\thetalasso</code>	$\boldsymbol{\theta}_{\text{LASSO}}$	theta (LASSO)
<code>\thetaols</code>	$\boldsymbol{\theta}_{\text{OLS}}$	theta (RIDGE)

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**ml-survival**

Macro	Notation	Comment
<code>\Ti</code>	$T^{(\#1)}$	??
<code>\Ci</code>	$C^{(\#1)}$	??
<code>\oi</code>	$o^{(\#1)}$	??
<code>\ti</code>	$t^{(\#1)}$	??
<code>\deltai</code>	$\delta^{(\#1)}$	
<code>\Lxdi</code>	$L(\boldsymbol{\delta}, f(\mathbf{x}))$	

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## ml-svm

Macro	Notation	Comment
<code>\sv</code>	$SV$	supportvectors
<code>\sl</code>	$\zeta$	slack variable
<code>\slvec</code>	$(\zeta^{(1)}, \zeta^{(n)})$	slack variable vector
<code>\sli</code>	$\zeta^{(\#1)}$	i-th slack variable
<code>\scptxi</code>	$\langle \boldsymbol{\theta}, \mathbf{x}^{(i)} \rangle$	scalar prodct of theta and xi
<code>\svmhplane</code>	$y^{(i)} (\langle \boldsymbol{\theta}, \mathbf{x}^{(i)} \rangle + \theta_0)$	SVM hyperplane (normalized)
<code>\alphah</code>	$\hat{\alpha}$	alpha-hat (basis fun coefficients)
<code>\alphav</code>	$\boldsymbol{\alpha}$	vector alpha (bold) (basis fun coefficients)
<code>\alphavh</code>	$\hat{\boldsymbol{\alpha}}$	vector alpha-hat (basis fun coefficients)
<code>\dualobj</code>	$\sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y^{(i)} y^{(j)} \langle \mathbf{x}^{(i)}, \mathbf{x}^{(j)} \rangle$	min objective in lin svm dual
<code>\HS</code>	$\Phi$	H, hilbertspace
<code>\phix</code>	$\phi(\mathbf{x})$	feature map x
<code>\phixt</code>	$\phi(\tilde{\mathbf{x}})$	feature map x tilde
<code>\kxxt</code>	$k(\mathbf{x}, \tilde{\mathbf{x}})$	kernel fun x, x tilde
<code>\scptxifm</code>	$\langle \boldsymbol{\theta}, \phi(\mathbf{x}^{(i)}) \rangle$	scalar prodct of theta and xi

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## ml-trees

Macro	Notation	Comment
<code>\Np</code>	$\mathcal{N}$	(Parent) node N
<code>\Npk</code>	$\mathcal{N}_k$	node N_k
<code>\Nl</code>	$\mathcal{N}_1$	Left node N_1
<code>\Nr</code>	$\mathcal{N}_2$	Right node N_2
<code>\pikN</code>	$\pi_{\#1}^{(\mathcal{N})}$	class probability node N
<code>\pikNh</code>	$\hat{\pi}_{\#1}^{(\mathcal{N})}$	estimated class probability node N
<code>\pikNlh</code>	$\hat{\pi}_{\#1}^{(\mathcal{N}_1)}$	estimated class probability left node
<code>\pikNr</code>	$\hat{\pi}_{\#1}^{(\mathcal{N}_2)}$	estimated class probability right node

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