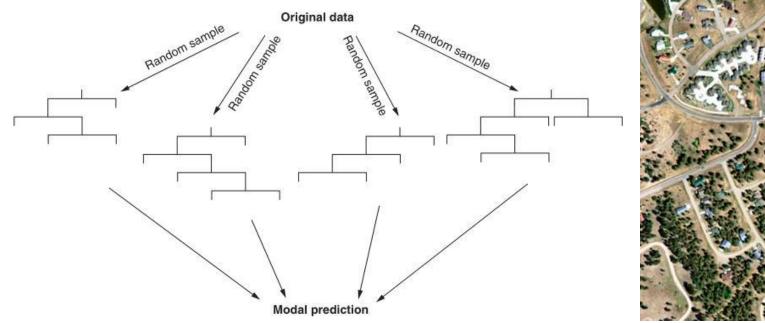
Land Use Land Cover Classification using Machine Learning Methods

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What is this course about?







```
rTask <- mlr::makeClassifTask(data = amostras_df, target = "class") # create task

rf = mlr::makeLearner("classif.randomForest", predict.type = "prob") # create learner

rfModel <- mlr::train(rf, rTask) # train the model

kFold <- mlr::makeResampleDesc("RepCV", folds = 10, reps = 50) # cross validation parameters

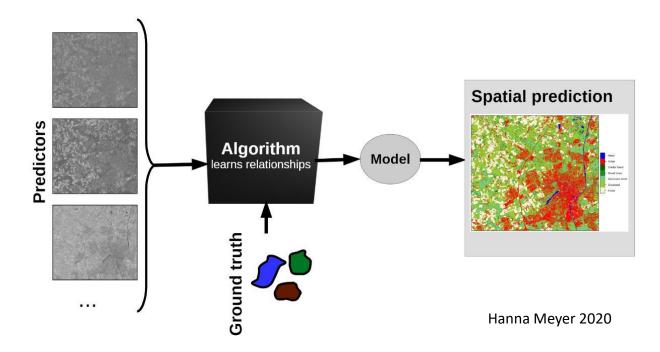
rfFoldCV <- mlr::resample(learner = rf, task = rTask, resampling = kFold, measures = list(mmce, kappa))</pre>
```

What will we learn?

- How to work with raster and vector data in R and Google Earth Engine
- How to get some good samples to train your model
- How to clean and prepare your data
- How to apply machine learning methods like Random Forest to classify satellite images
- How to improve your model
- How to validate your results
- Export and visualize output data



So...the main idea is to...



- First get some good input satellite image to serve as predictor variables
- Collect good samples to train the model
- Train the model to do some tests to improve even more the final results
- Use the model to classify the satellite raster data and create a beautiful final land use map :-)

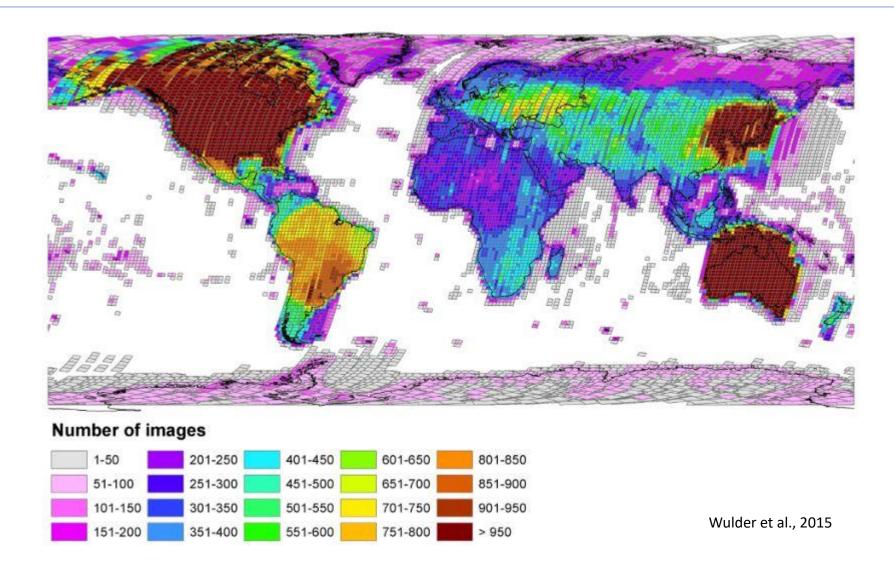


About the input data: examples of available satellite/sensor data

Platform/Sensor	Spatial Resolution	Temporal Resolution	Availability
Landsat MSS	79	16 days	started in 1972
Landsat TM	30	16 days	started in 1982
Landsat ETM+	30	16 days	started in 1999
Landsat 8 OLI	30	16 days	started in 2013
Landsat 9 OLI-2	30	16 days	mid 2021
Sentinel 2	10-20	5/10 days	started in 2014
MODIS	250-1000	4 per day	started in 2000

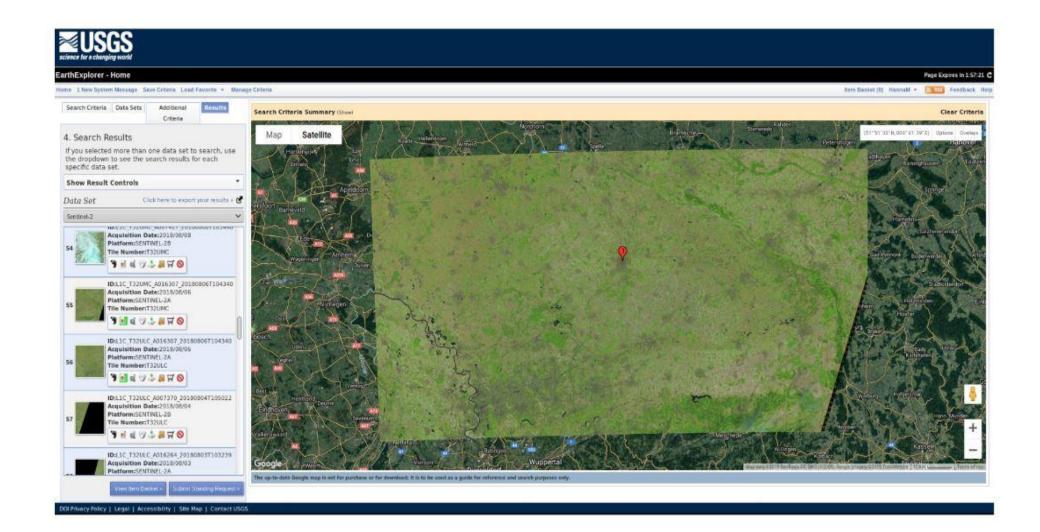


Accessible Landsat data



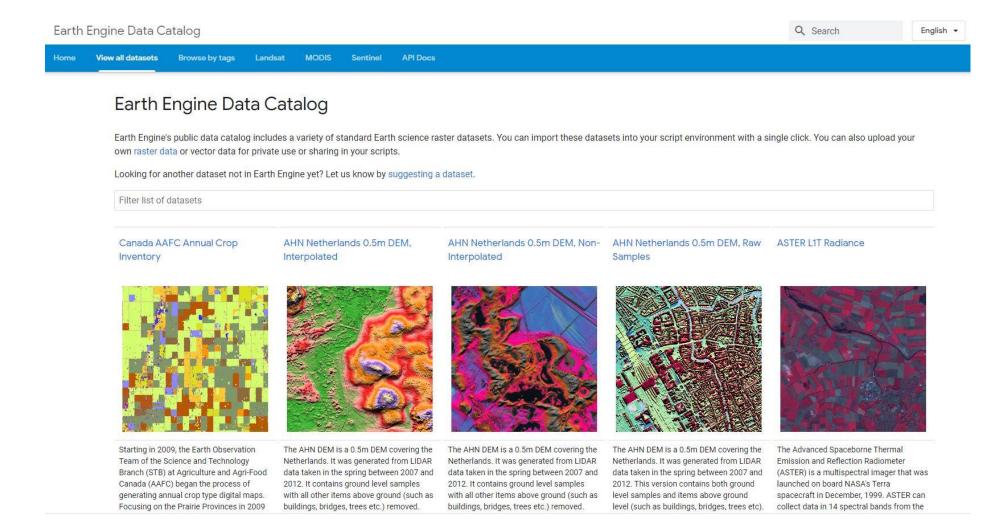


And how we can access them?





And how we can access them?



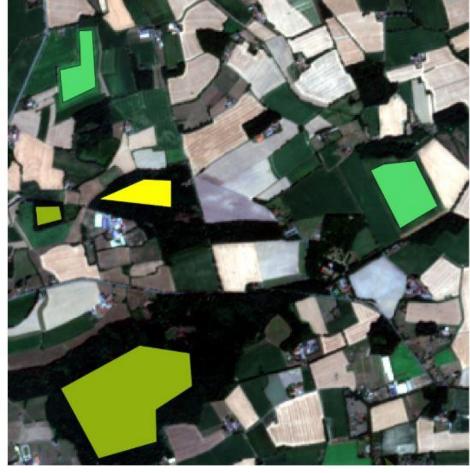


I downloaded the image. What do I do now?





Polygon data





Now we choose the algorithm to use

There are many options...

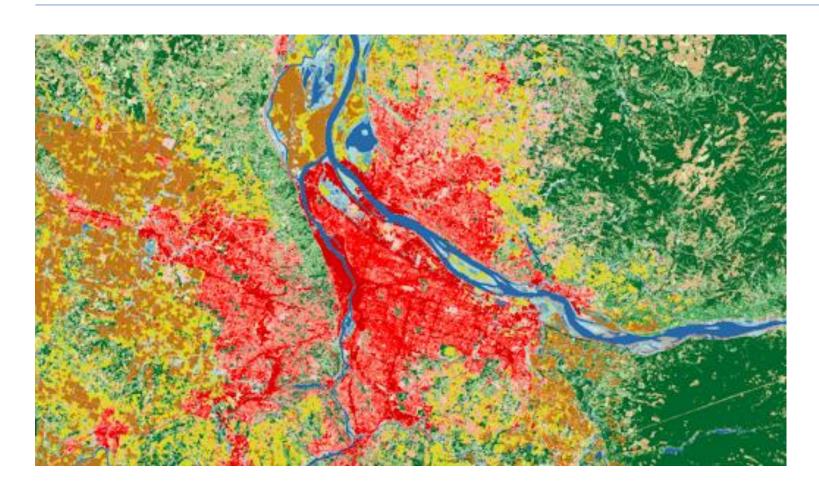
→ ee.Classifier

- ee.Classifier.cart(crossvalidationFactor, maxDepth, minLeafPopula...
- ee.Classifier.decisionTree(treeString)
- ee.Classifier.decisionTreeEnsemble(treeStrings)
- ee.Classifier.gmoMaxEnt(weight1, weight2, epsilon, minIterations, ...
- ee.Classifier.libsvm(decisionProcedure, svmType, kernelType, shri...
- ee.Classifier.minimumDistance(metric)
- ee.Classifier.naiveBayes(lambda)
- ee.Classifier.randomForest(numberOfTrees, variablesPerSplit, min...
- ee.Classifier.smileCart(maxNodes, minLeafPopulation)
- ee.Classifier.smileNaiveBayes(lambda)
- ee.Classifier.smileRandomForest(numberOfTrees, variablesPerSpl...
- ee.Classifier.spectralRegion(coordinates, schema)
- ee.Classifier.svm(decisionProcedure, svmType, kernelType, shrinki...



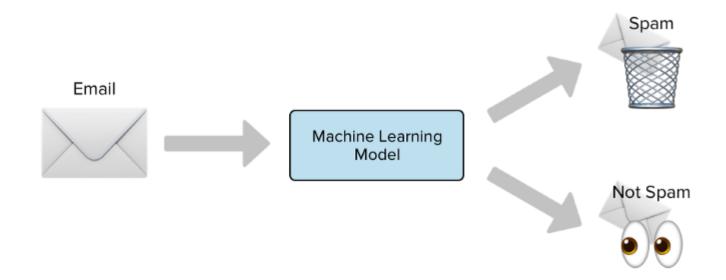
*	class	† name † si	nort.name	package
1	classif.ada	ada Boosting	ada	ada,rpart
2	classif.adaboostm1	ada Boosting M1	adaboostm1	RWeka
3	classif.bartMachine	Bayesian Additive Regression Trees	bartmachine	bartMachine
4	classif.binomial	Binomial Regression	binomial	stats
5	classif.boosting	Adabag Boosting	adabag	adabag,rpart
6	classif.bst	Gradient Boosting	bst	bst,rpart
7	classif.C50	C50	C50	C50
8	classif.cforest	Random forest based on conditional inference trees	cforest	party
9	classif.clusterSVM	Clustered Support Vector Machines	clusterSVM	SwarmSVM,Liblinea
10	classif.ctree	Conditional Inference Trees	ctree	party
11	classif.cvg/mnet	GLM with Lasso or Elasticnet Regularization (Cross Validated	cvg/mnet	glmnet
12	classif.dbnDNN	Deep neural network with weights initialized by DBN	ialized by DBN dbn.dnn	
13	classif.dcSVM	Divided-Conquer Support Vector Machines	dcSVM	SwarmSVM,e1071
14	classif.earth	Flexible Discriminant Analysis	fda	earth,stats
15	classif.evtree	Evolutionary learning of globally optimal trees	otimal trees evtree	
16	classif.extraTrees	Extremely Randomized Trees	extraTrees	extraTrees
17	classif.fdausc.glm	Generalized Linear Models classification on FDA	fdausc.glm	fda.usc
18	classif.fdausc.kernel	Kernel classification on FDA	fdausc,kernel	
19	classif.fdausc.knn	fdausc.knn	fdausc.knn	fda.usc
20	classif.fdausc.np	Nonparametric classification on FDA	fdausc.np	fda.usc
21	classif.featureless	Featureless classifier	featureless	mir
22	classif.fnn	Fast k-Nearest Neighbour	fnn	FNN
23	classif.gamboost	Gradient boosting with smooth components	th smooth components gamboost	
24	classif.gaterSVM	Mixture of SVMs with Neural Network Gater Function	gaterSVM	SwarmSVM

Output data



- Urban
- Forest
- Bare Soil
- Grasslands
- Pasture
- Others?







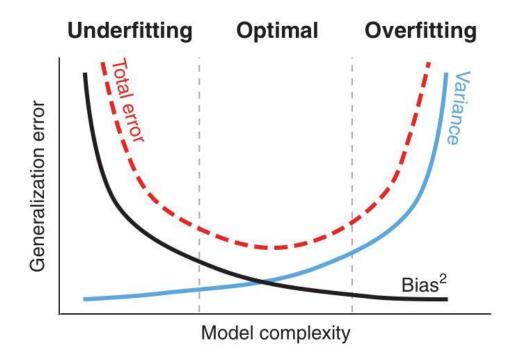
Underfitting and **Overfitting** are two important sources of error in model building. It also reduce the *generalizability* of our model.

Underfitted – Your model is too simple and is biased towards misclassifying certain types of classes. A model that is underfitted will perform poorly on both the data we use to train it and with new data.

Overfitted – Your model is too complex and is modeling noise in the data that you used to train it. A model that is overfitted will perform well on the data used to train it, but poorly on new data. So, that not good!

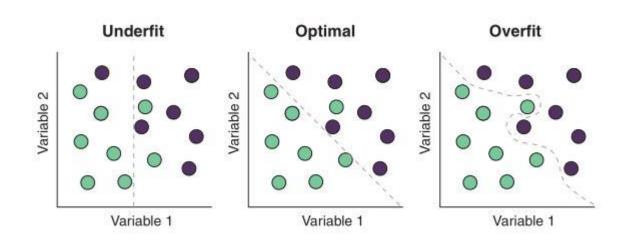
With overfitting we are modeling noise. And the pattern of noise is very specific to an individual dataset!





- Generalization error is the proportion of erroneous predictions a model makes and is a result of overfitting and underfitting.
- The error associated with overfitting (too complex a model) is variance.
- The error associated with underfitting (too simple a model) is bias.
- An optimal model balances this trade-off.





- The dotted line represents a decision boundary (model)
- The more complex model is more likely to moss local differences in our data!
- So, how can I tell if I'm underfitting or overfitting?
 The question is a technique called cross-validation.



The solution is to evaluate the performance of our model using data that the model hasn't seen yet! We can do that collection future data, but its better to just split the training set as training and test set.

Doing that we can use some performance metrics to show how well the model will perform on unseen data.

Types of cross-validation

- Holdout cross-validation
- K-fold cross-validation
- Leave-one-out cross-validation



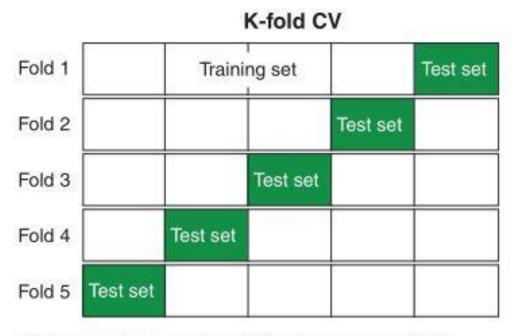
Holdout CV

Training set

Test set

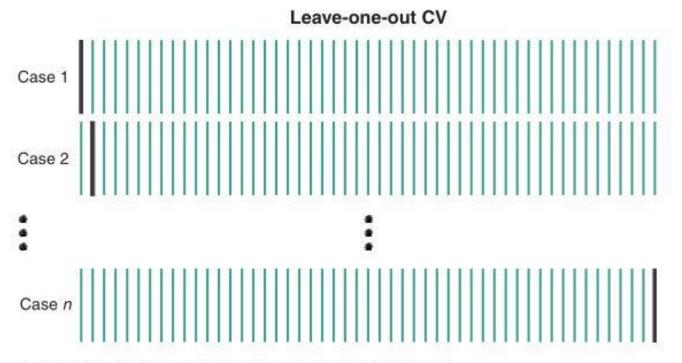
- The data is randomly split into a training and test set.
- A model is trained using only the training set.
- Predictions are made on the test set.
- The predictions are compared to the true values.

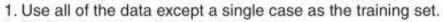




- 1. The data is randomly split into *k* equal-sized folds.
- Each fold is used as the test set once, where the rest of the data makes the training set.
- 3. For each fold, predictions are made on the test set.
- 4. The predictions are compared to the true values.



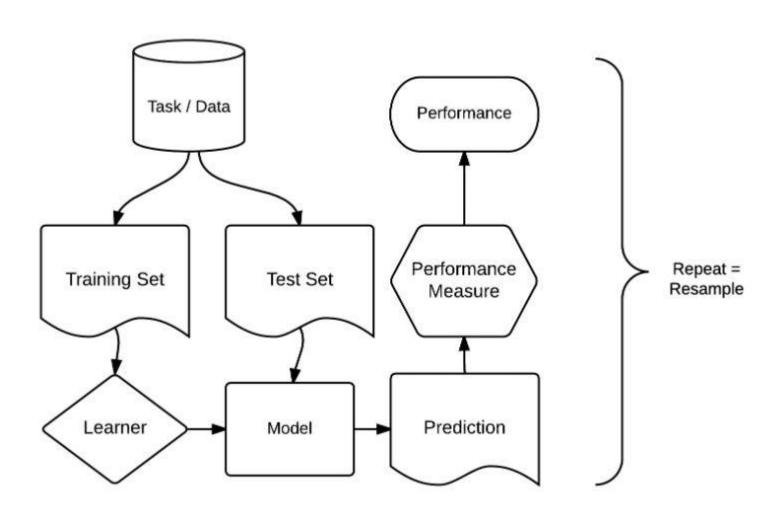




- 2. Predict the value of the single test case.
- 3. Repeat until every case has been the test case.
- 4. The predictions for each case are compared to the true values.



The typical workflow

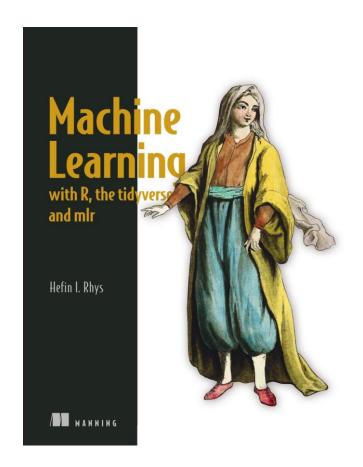




Practice time!



Extra material



Decision Trees:

https://www.youtube.com/watch?v=7VeUPuFGJHk&ab_channel=StatQuestwithJoshStarmer

Random Forest:

https://www.youtube.com/watch?v=J4Wdy0Wc_xQ&t=7s&ab_channel=StatQuestwithJoshStarmer

https://www.youtube.com/watch?v=nyxTdL_4Q-Q&ab_channel=StatQuestwithJoshStarmer



Extra material

MLR documentation:

https://arxiv.org/pdf/1609.06146.pdf

MLR3 documentation:

https://mlr3book.mlr-org.com/

Tidymodels:

https://www.tidymodels.org/

https://www.tmwr.org/

