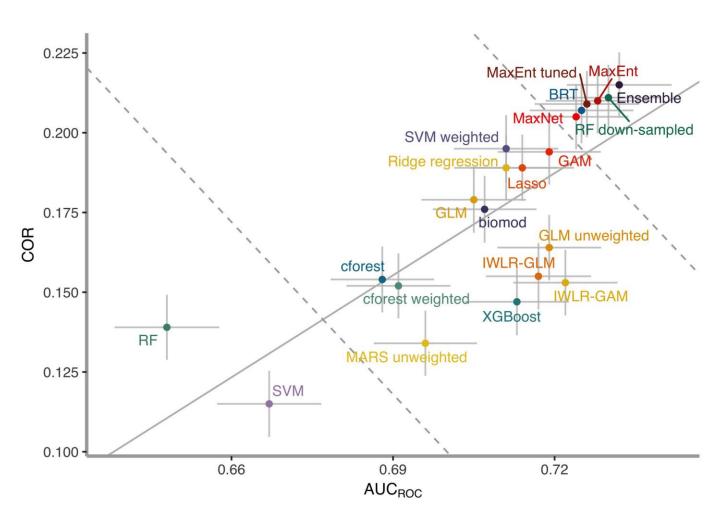
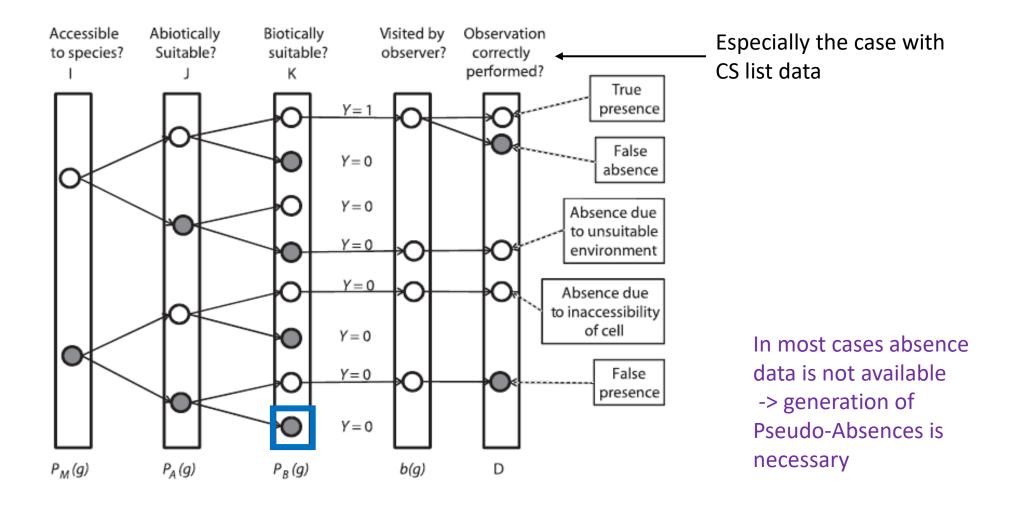
# (Pseudo-)Absences for Species distribution modelling

# Why do we need them?



# The problem with absence data



- background data: characterise the whole landscape
  - sample points to shorten the computational time
  - risk of introducing false absences (Anderson, 2010)
  - overfitting to conditions found near the presences (Anderson, 2010)
  - inflate test statistics (Iturbide et al., 2015)
- pseudo-absence data: characterise the landscape where the species does not occur
  - a priori decisions about the suitability of regions needed (may influence the modelling results) (Stokland et al., 2011)
- **study region:** restricted calibration area + prediction into the larger study area leads to more realistic predictions (Anderson, 2010)
  - extrapolation occurs mainly in regions where presence is unlikely
  - delineation based on topography or coarse distributional patterns
- Background/PA data can be sampled with the same geographic bias as the training data (Phillips et al., 2009) -> but: many assumptions

# Strategies for sampling of pseudo-absences

- sampling within areas that are
  - at a geographical distance from the training points or
  - environmental dissimilar to the training points (Senay et al., 2013)
- distance in geographical space:
  - choosing the ideal distance based on the model performance (trial and error)
  - based on expert knowledge
  - based on telemetry data derived movement characteristics
- distance in environmental/predictor space:
  - identification of least suitable areas using presence-only methods
  - based on expert knowledge

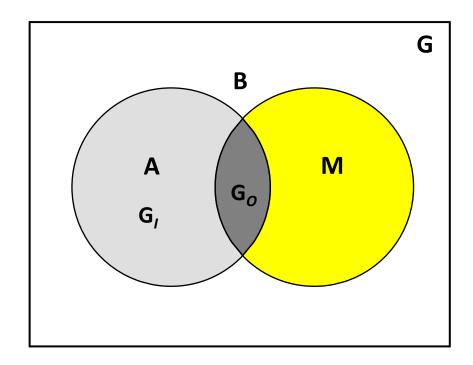
# Strategies for sampling of pseudo-absences

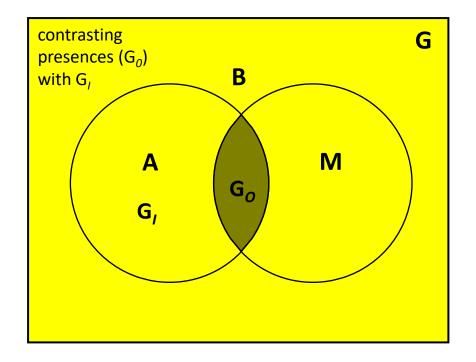
- Three step method (Senay et al., 2011):
  - 1. Specify geographical extent:
    - increasing the distance until the contribution of the most important variable decreases
  - 2. Classify these areas based on their environmental similarity to presence sites
    - no similarity -> potential pseudo-absence points
  - 3. Cluster these areas in environmental space
    - number of clusters = number of presences available
    - centroids of the clusters are projected into geographical space
       pseudo-absence points
- R-package mopa (Iturbide et al., 2015): provides 3-step PA-sampling method
  - Pseudo-Absences provide generally higher AUC than background points; but: poor CVstrategy + weak test metric

# Strategies for sampling of PA / BG data

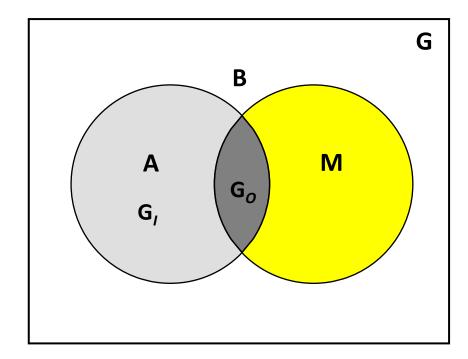
- package *flexsdm*:
  - background points:
    - random
    - thickening: more sampling towards presence sites
    - bias: using raster layer representing sampling effort
  - pseudo-absence points:
    - random
    - env\_const: distance in environmental space
    - geo\_const: distance in geographical space
    - geo\_env\_const: combination of geo & env constrained (2-step)
    - geo\_env\_km\_const: + distributing PAs in env-space using k-means (3-step)

pseudo-absence data: estimation of the potential distribution (ENM) (Iturbide et al., 2015) background data: estimation of the realized distribution (SDM) (Iturbide et al., 2015)





- Calibration area: should be restricted to the area that is accessible to the species (M)
  - Distinction between PA & BG-data difficult



Algorithms	Туре	Weighting
Maxent, BRT, ENFA	BG [1]; BRT: see RF [2]	unequal
Random Forest	BG [1] or PAg (when small sample size) [2] or PAe (when sample size is large) [2] class overlap -> better PA?	equal weight by down- sampling of bg-points
GLM, GAM	PAg [2;3] (when climatically biased* presences) or BG [3]	equal weight
ANN, SVM, NB	pseudo-absence	

\*can result from spatially biased sampling / when not the whole range of suitable environmental conditions was sampled [2]

[1] Valavi et al. (2021)

[2] Barbet-Massin et al. (2011)

[3] Senay et al. (2011)

**BG:** Background-Points

PAg: Pseudo-Absence points based on distance in

geographical space

PAe: Pseudo-Absence points based on distance in

environmental space