Habitat Classification and Species Distribution Modeling

Dean Urban

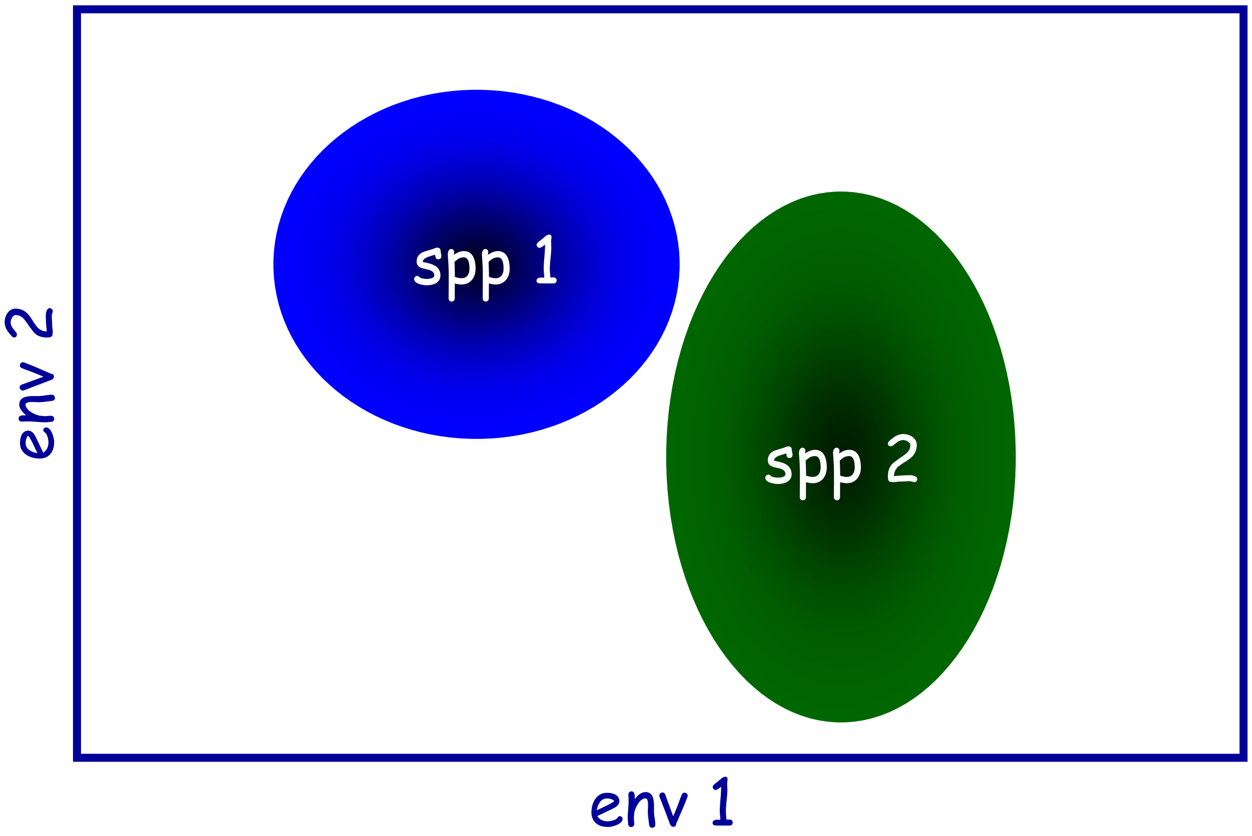
Spring 2012

Habitat classification and modeling

- Habitat models underpin most of natural resource management
  - Wildlife management
  - Conservation planning
  - Assessing future scenarios (climate!)

the Hutchinsonian niche

Issues:
- max overlap?
- packing?
- relevant axes?



Three interconnected models

Austin (2002, 2007):

- **Ecological model**
  - What we expect, and why
- **Data model**
  - What we measure, and why ← **GIS**
- **Statistical model**
  - How we "fit" ecology to data

Ecological models: scaling

- **Fine scale**: community ecology
  - Ecology is about niche theory
- **Landscape scale**:
  - Ecology is about area, edge, isolation, ...
- **Larger scales**: biogeography
  - Ecology is about evolutionary history, ...

Data models: variables

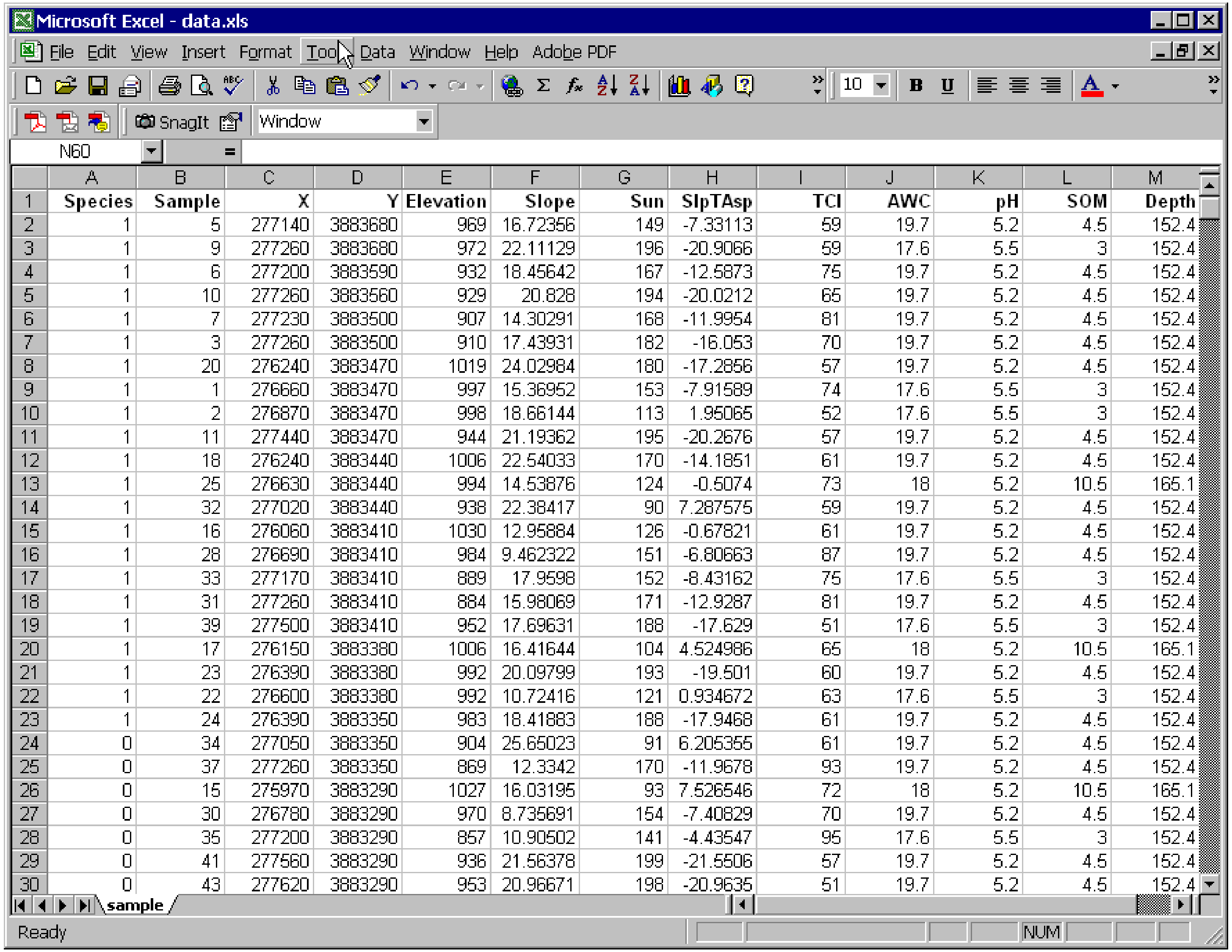
- Field studies:
  - Choose variables based on ecology

- Landscapes:
  - Geospatial data in a GIS, especially **biophysical proxies** (select variables based on conceptual model)
  - Beware spatial resolution!

Data models: coding

Cols = variables
(Species = 0/1)

Rows = samples

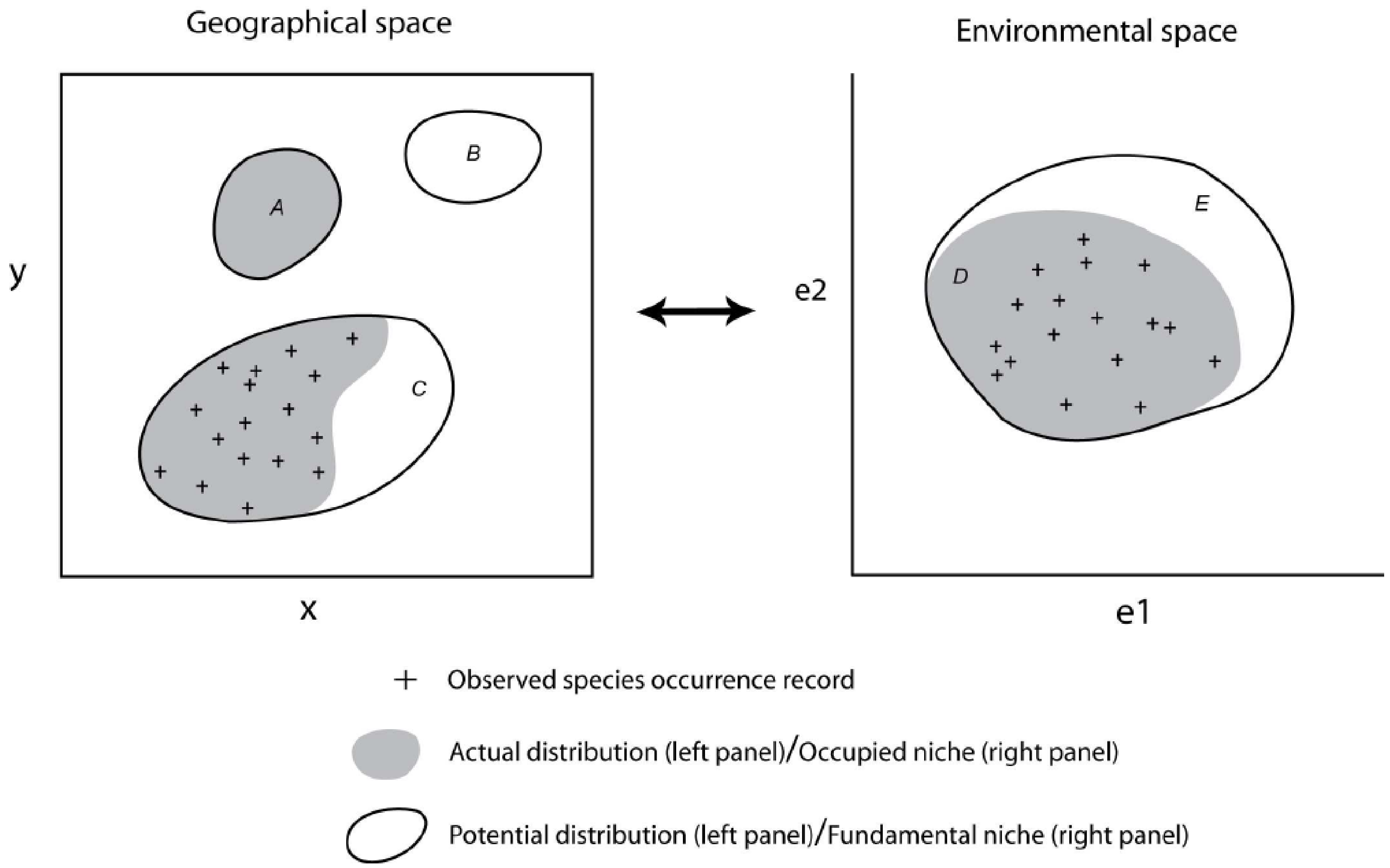


	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Species	Sample	X	Y	Elevation	Slope	Sun	SlpTAsp	TCI	AWC	pH	SOM	Depth
2	1	5	277140	3883680	969	16.72356	149	-7.33113	59	19.7	5.2	4.5	152.4
3	1	9	277260	3883680	972	22.11129	196	-20.9066	59	17.6	5.5	3	152.4
4	1	6	277200	3883590	932	18.45642	167	-12.5873	75	19.7	5.2	4.5	152.4
5	1	10	277260	3883560	929	20.828	194	-20.0212	65	19.7	5.2	4.5	152.4
6	1	7	277230	3883500	907	14.30291	168	-11.9954	81	19.7	5.2	4.5	152.4
7	1	3	277260	3883500	910	17.43931	182	-16.053	70	19.7	5.2	4.5	152.4
8	1	20	276240	3883470	1019	24.02984	180	-17.2856	57	19.7	5.2	4.5	152.4
9	1	1	276660	3883470	997	15.36952	153	-7.91589	74	17.6	5.5	3	152.4
10	1	2	276870	3883470	998	18.66144	113	1.95065	52	17.6	5.5	3	152.4
11	1	11	277440	3883470	944	21.19362	195	-20.2676	57	19.7	5.2	4.5	152.4
12	1	18	276240	3883440	1006	22.54033	170	-14.1851	61	19.7	5.2	4.5	152.4
13	1	25	276630	3883440	994	14.53876	124	-0.5074	73	18	5.2	10.5	165.1
14	1	32	277020	3883440	938	22.38417	90	7.287575	59	19.7	5.2	4.5	152.4
15	1	16	276060	3883410	1030	12.95884	126	-0.67821	61	19.7	5.2	4.5	152.4
16	1	28	276690	3883410	984	9.462322	151	-6.80663	87	19.7	5.2	4.5	152.4
17	1	33	277170	3883410	889	17.9598	152	-8.43162	75	17.6	5.5	3	152.4
18	1	31	277260	3883410	884	15.98069	171	-12.9287	81	19.7	5.2	4.5	152.4
19	1	39	277500	3883410	952	17.69631	188	-17.629	51	17.6	5.5	3	152.4
20	1	17	276150	3883380	1006	16.41644	104	4.524986	65	18	5.2	10.5	165.1
21	1	23	276390	3883380	992	20.09799	193	-19.501	60	19.7	5.2	4.5	152.4
22	1	22	276600	3883380	992	10.72416	121	0.934672	63	17.6	5.5	3	152.4
23	1	24	276390	3883350	983	18.41883	188	-17.9468	61	19.7	5.2	4.5	152.4
24	0	34	277050	3883350	904	25.65023	91	6.205355	61	19.7	5.2	4.5	152.4
25	0	37	277260	3883350	869	12.3342	170	-11.9678	93	19.7	5.2	4.5	152.4
26	0	15	275970	3883290	1027	16.03195	93	7.526546	72	18	5.2	10.5	165.1
27	0	30	276780	3883290	970	8.735691	154	-7.40829	70	19.7	5.2	4.5	152.4
28	0	35	277200	3883290	857	10.90502	141	-4.43547	95	17.6	5.5	3	152.4
29	0	41	277560	3883290	936	21.56378	199	-21.5506	57	19.7	5.2	4.5	152.4
30	0	43	277620	3883290	953	20.96671	198	-20.9635	51	19.7	5.2	4.5	152.4

Data spaces and translations

- Field data, map data are in *geographic space*
- Statistics translate these into *parameter space*
- Often, we will want to back-translate the statistics into a map (the locations are what's interesting)

Data spaces and translations


Geographical space
Environmental space
A
B
C
D
E
y
x
e2
e1
+ Observed species occurrence record
Actual distribution (left panel)/Occupied niche (right panel)
Potential distribution (left panel)/Fundamental niche (right panel)

Pearson 2008

Statistical models: preamble

Caveats:

- Once the data are coded, the statistics are blind to ecology
- The onus in on the investigator to put the ecology back on completion, for interpretation

Statistical models

Data models: observations

Kinds of locational observations:

1. Where you saw species X ("habitat")
2. Where you looked but didn't see it ("nonhabitat")
3. Where it *might* have occurred ("available habitat")

→ All statistical models proceed from some combination of these data

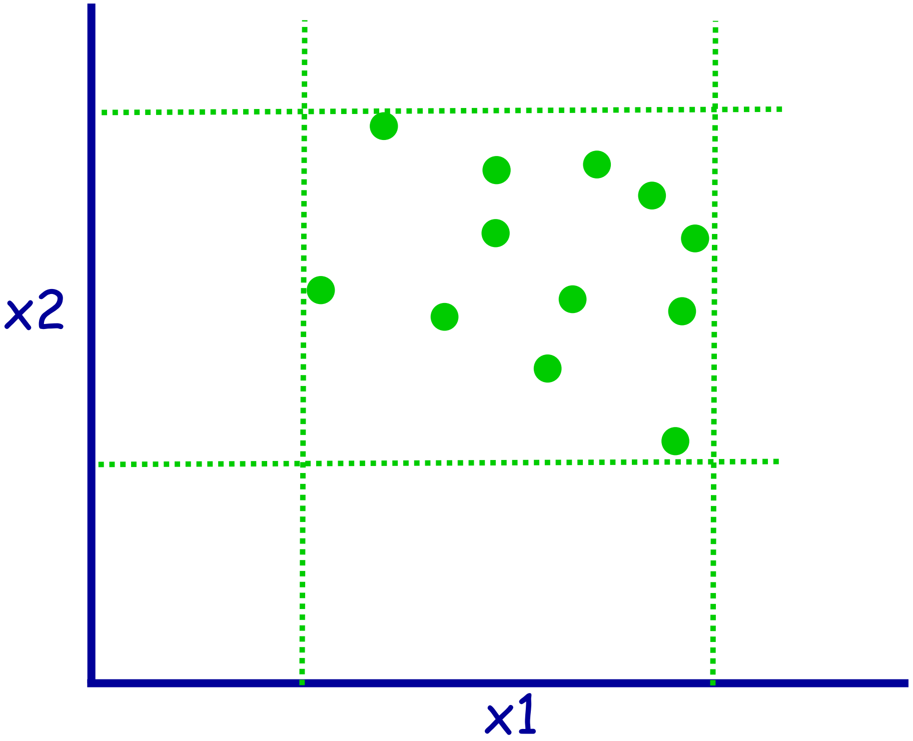
Statistical models: logic

- “Habitat” cf “nonhabitat” – are these 2 samples different on the predictors?

- “Habitat” cf “available habitat” – is this sample different from a random draw of what *might* have been observed?

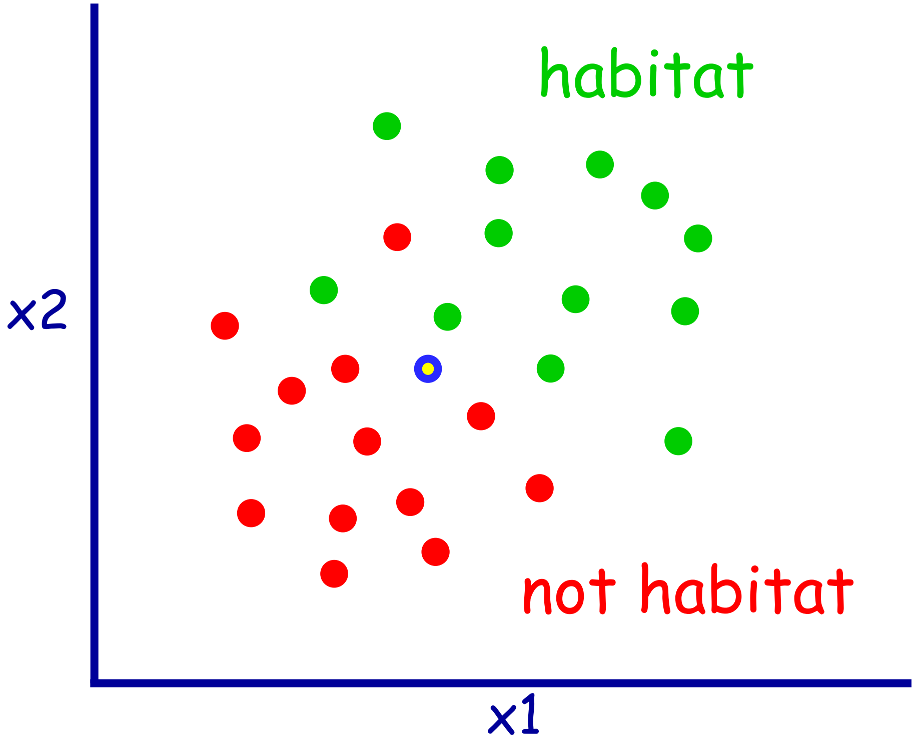
- 1-sample “habitat” – show me all the places that *look* like “habitat”

Generative models: “envelopes“



- Define limits in terms of lower and upper bounds (or some arbitrary confidence ellipse)
- Simple and easy!

Discriminative models: logic

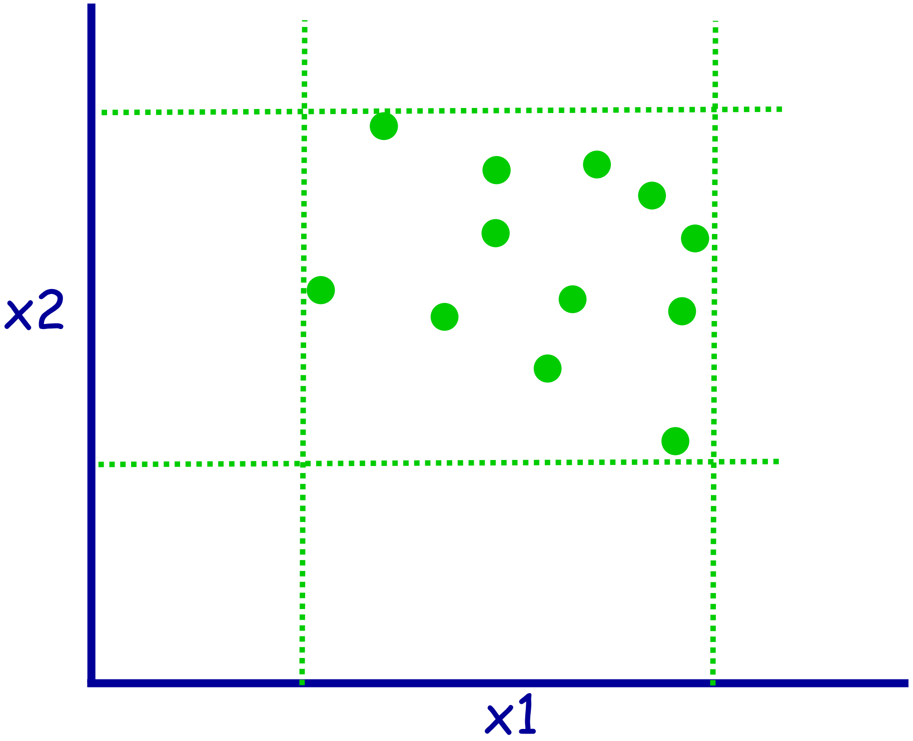


- Q: what function of X1 and X2 best separates the 2 groups?
- A: provided by several alternative statistical methods

Models: tour guide

- There are multiple approaches to this task—each represented by a few techniques
- For each:
    - What does it do?
    - Advantages and disadvantages
    - Current status (popularity)
- Relationships among techniques

Statistical models: (1) “envelopes“

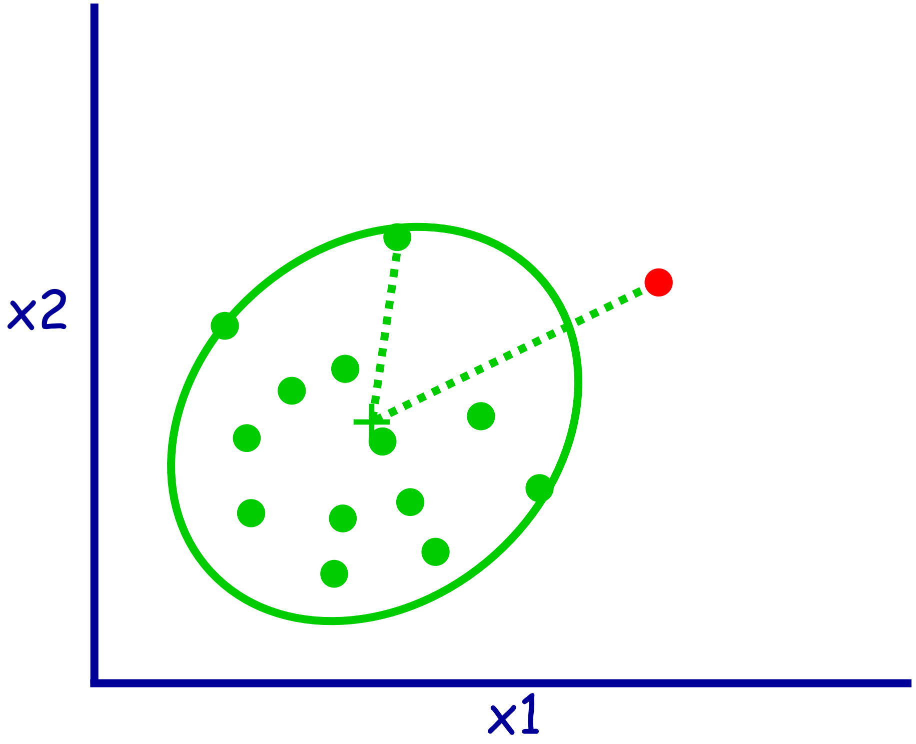


- Define limits in terms of lower and upper bounds (or some arbitrary confidence ellipse)

Envelopes: summary

- *Advantages:*
  - Simple (especially in GIS)
  - Can use any data (or none!)
- *Disadvantages:*
  - Poor leverage statistically (presence only)
- *Status:*
  - Common and popular
  - Fancy extensions (GARP, DOMAIN, …)

Envelopes: Mahalanobis D^2



- D^2 = (squared) distance from group centroid (accounting for any correlation among the x's)

→ How much does this sample look like "habitat"?

Envelopes: Mahalanobis D^2

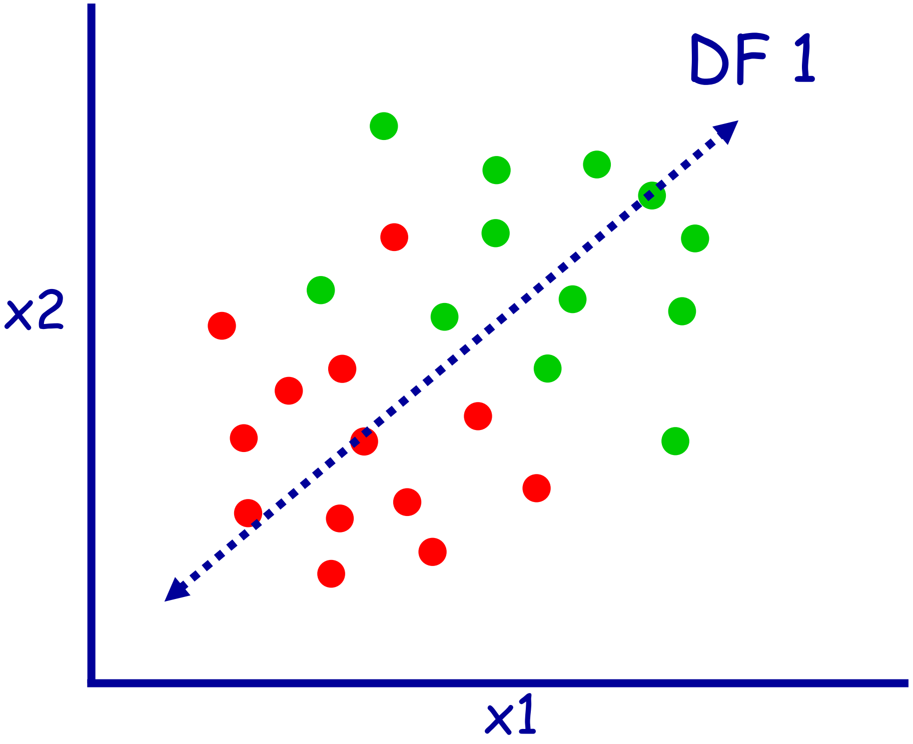
- *Advantages:*
  - Requires only “habitat” data
  - Can be “tuned” to application
- *Disadvantages:*
  - Requires ratio-scale data
  - Hard to interpret variables
- *Status:*
  - Resurgence in mapping applications
  - The “classifier” in supervised methods

Statistical models: (2) DFA

Discriminant functions analysis

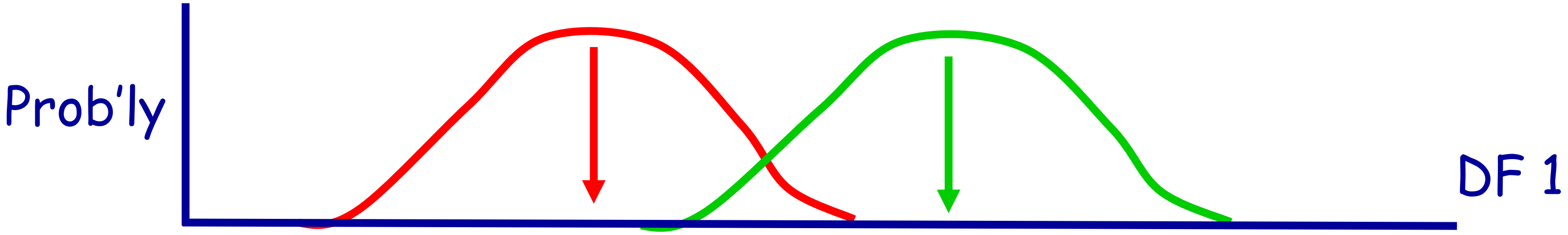
- Finds the best linear function of the original (predictor) variables that separates the 2 groups
- Maximizes among-group to within-group variability on this function

DFA: logic



- DF 1 maximally separates the groups
- Note (here) neither X1 nor X2 can separate the groups by itself

DFA: interpretation



- DFA tests separation of the group means
- Correlations between DFs and original variables provide for interpretation
- Classification is based on a (new) sample's proximity to each group mean

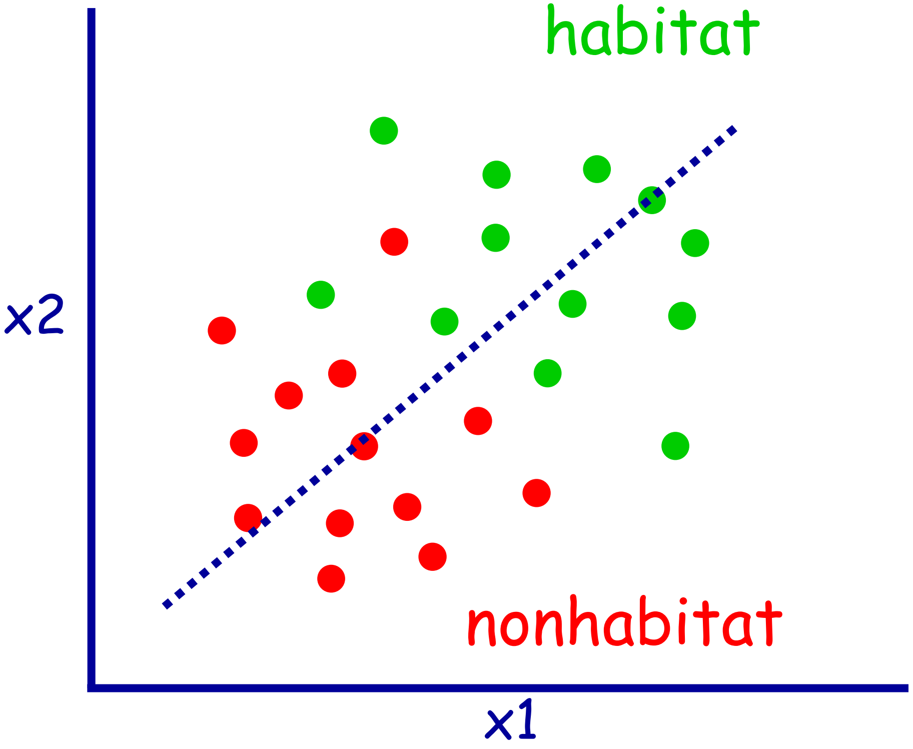
DFA: summary

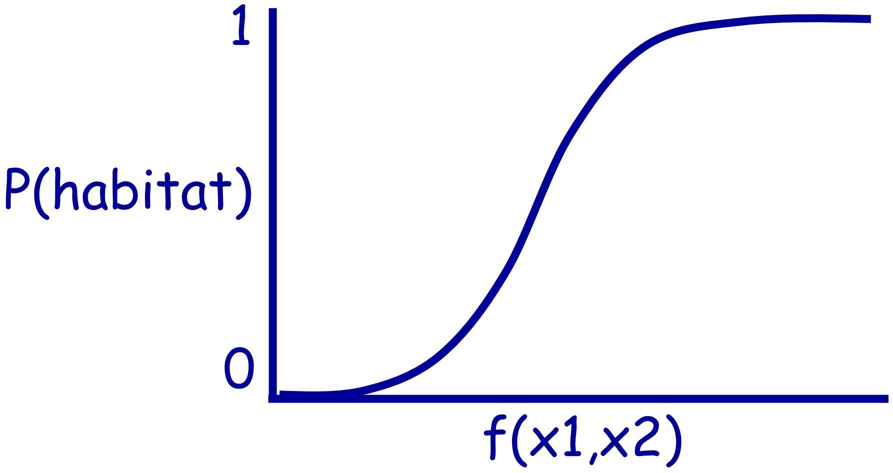
- *Advantages:*
  - Does what we want!
- *Disadvantages:*
  - assumes multi-normality
  - the variables are ratio scale
  - the functions are linear
- *Status:*
  - new versions (robust, quadratic, flexible)

Statistical models: (3) GLMs

- Linear model:
  - Y = b0 + b1x1 + b2x2 + … + error
- Generalized linear model:
  - U = b0 + b1x1 + b2x2 + … + error
  - Y = link function of U
  - Link function maps the linear term to the distribution of the data

GLMs: Logistic regression





habitat = 1; not = 0

GLMs: Logistic regression

- Logit model:

$$P(\text{habitat}) = e^u/(1+e^u)$$

where

$$u = f(x1, x2, \ldots)$$

so

$$\ln[P(\text{habitat})/P(\text{not})] = u$$

GLMs: summary

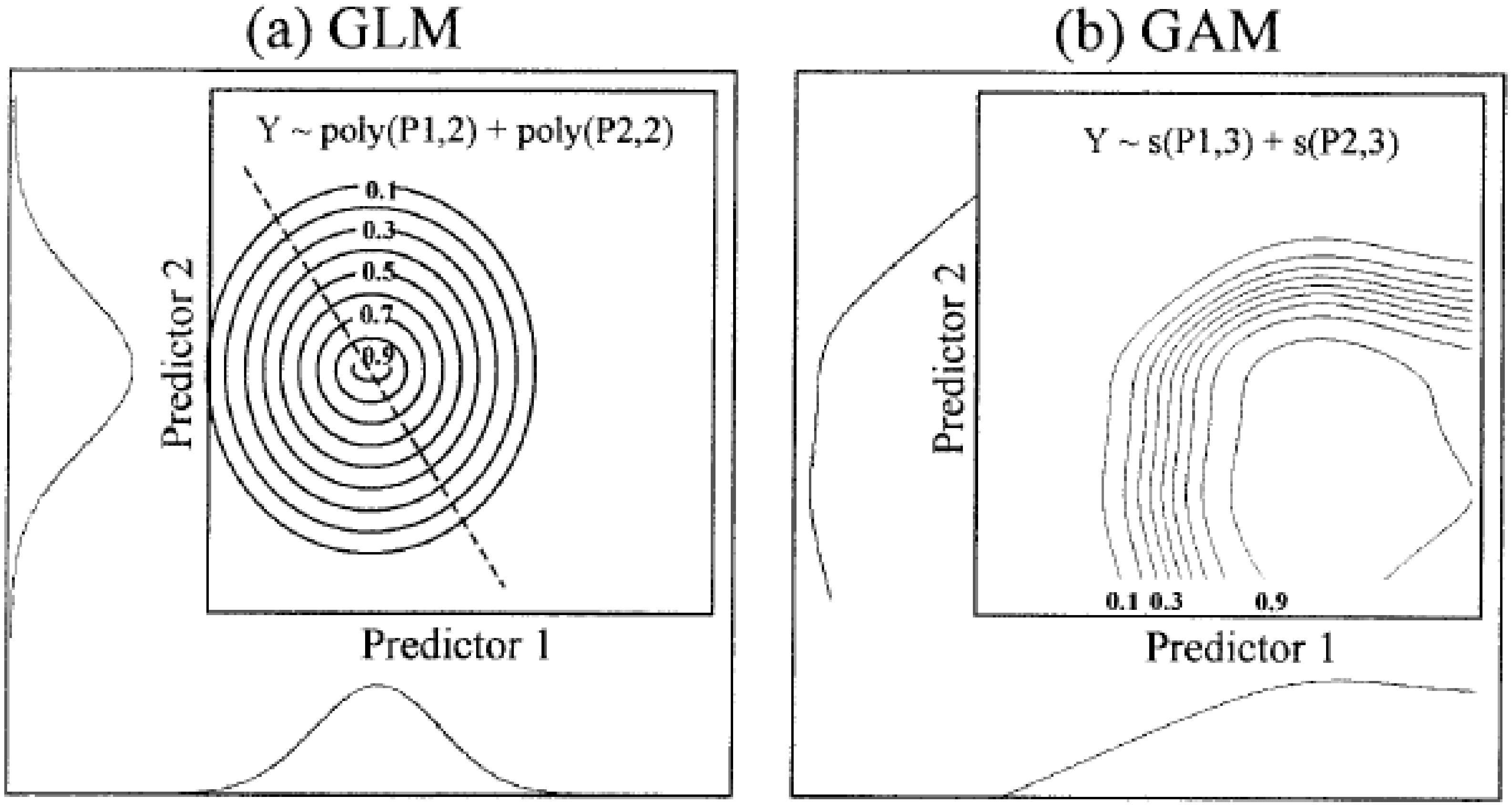
- *Advantages:*
  - Lots of distributions and link functions
  - Can use mixed data types
  - Can be “tuned” as a predictor
- *Disadvantages:*
  - (it’s still a regression)
- *Status:*
  - the workhorse model

GLMs: extensions

Extensions to the basic GLM …

- GAM:
  - b's become smoothing functions
- GLMM, GEE (mixed models):
  - Spatial structure (distributions) OK
- MARS
  - Multivariate adaptive GLMs

GLM vs GAM

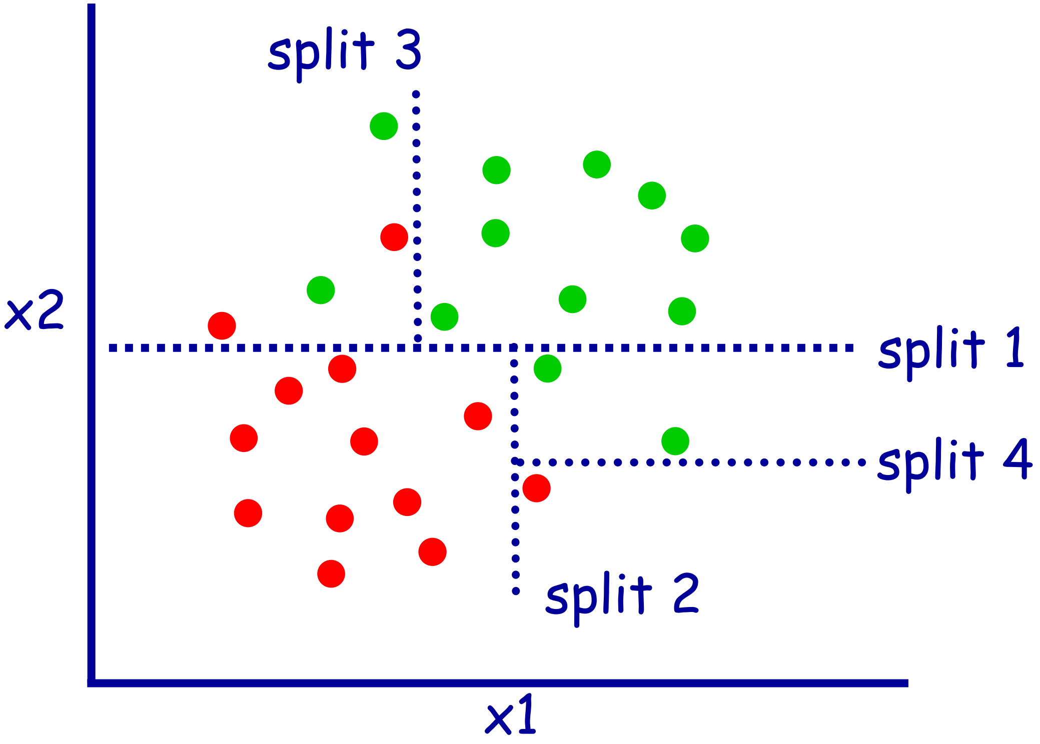


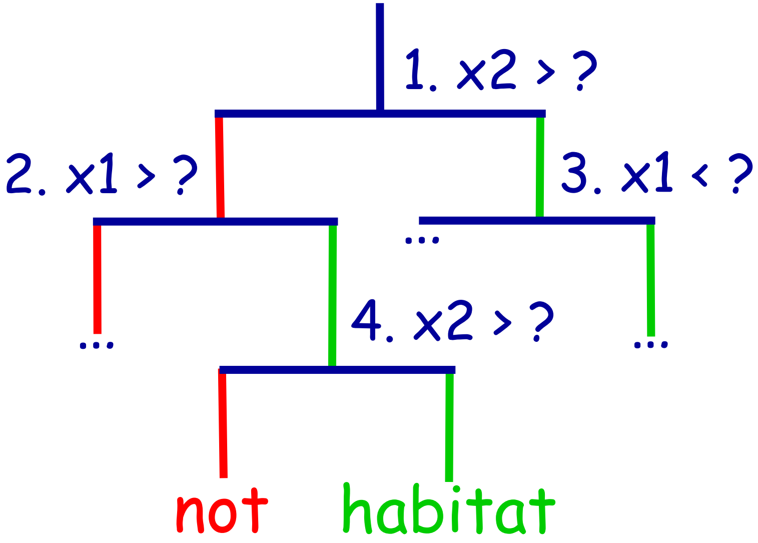
A. Guisan, N.E. Zimmermann / Ecological Modelling 135 (2000) 147–186

Statistical models: (4) CART

- Consider: "sugar pine is found at middle elevations on mesic slopes; also at lower elevations on NE slopes of in pockets of deep soil, or at higher elevations on SW slopes …"
- Need a model that can handle compensatory, substitutable settings: a classification (or regression) tree

CART: logic


split 3
x2
split 1
split 4
split 2
x1


1. x2 > ?
2. x1 > ?
3. x1 < ?
...
...
4. x2 > ?
...
not
habitat

CART: summary

- *Advantages:*
  - Can handle complex complementary or substitutable cases
  - Can use any data types
  - Provides intuitive decision tree
- Disadvantages:
  - Over-fitting (unstable)
- *Status:*
  - Extensions are popular

CART: extensions

Extensions to CART:

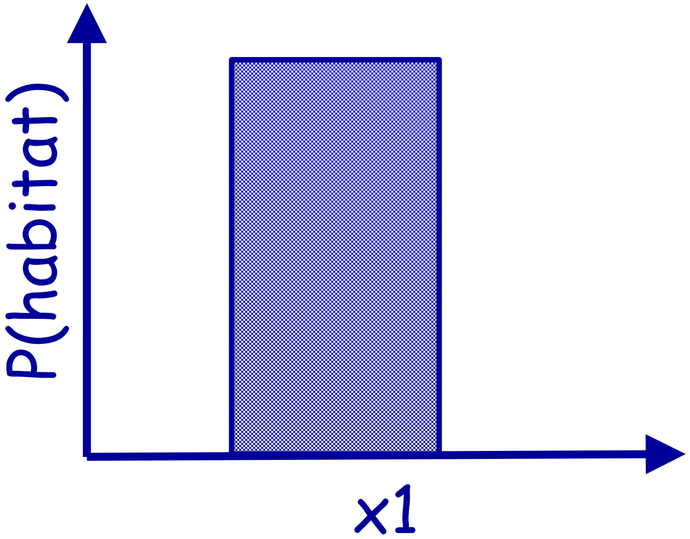
- “Bagged” trees
  - Resampled, then averaged
- “Boosted” trees
  - Resampled and re-weighted; averaged
- Random forests
  - Resampled observations & predictors; averaged (1000’s of trees)

Statistics: (5) Maximum entropy

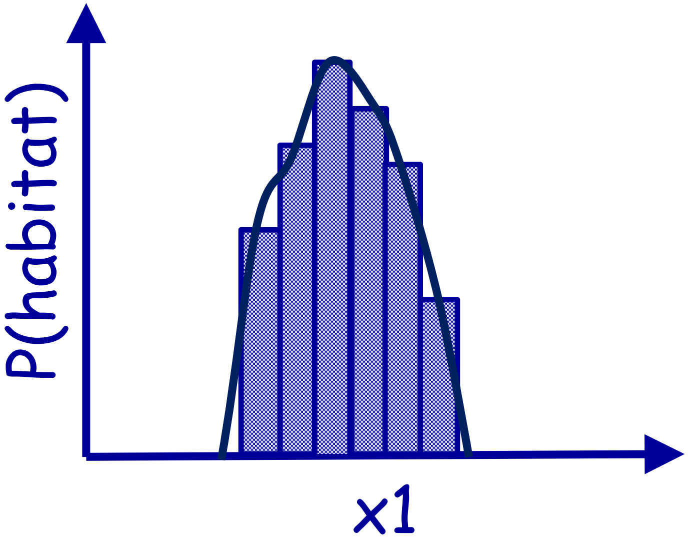
- Goal: find a distribution function that describes the data as closely as possible (an “envelope” model)
- Theory: the function that does this is the one with maximum entropy while also meeting specified constraints

Maximum entropy: logic

Envelope model:

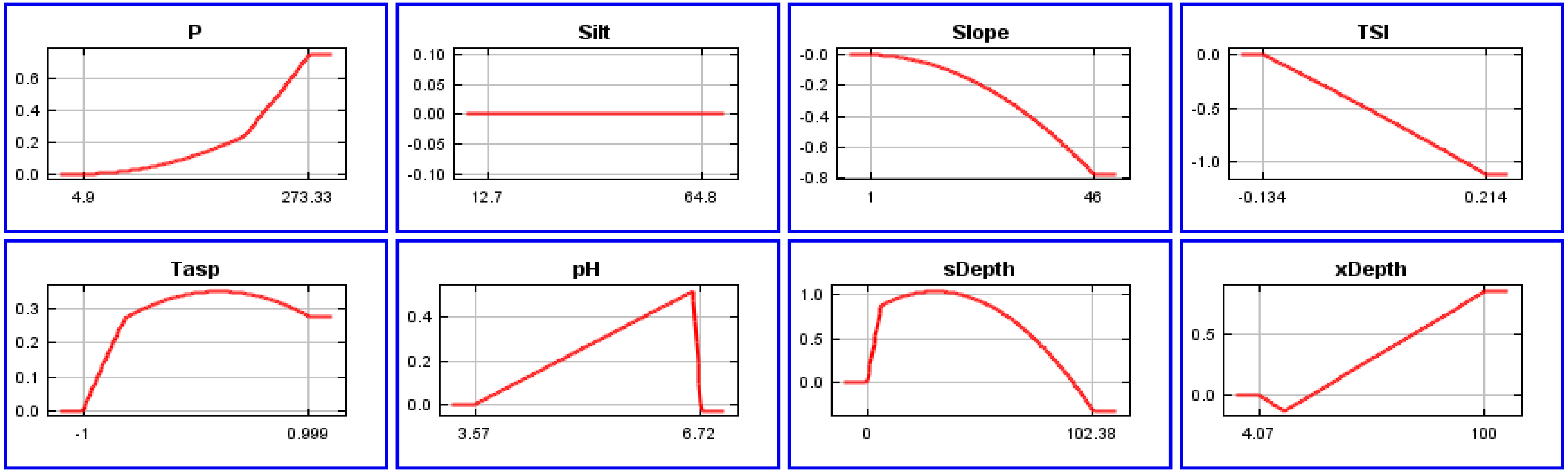


Maxent model:



Maxent: estimation (cf GAM)

- Examples of maxent features: piecewise “features” of the variables (categorical, linear, quadratic, threshold, hinges, interactions)



Maxent: estimation (maxent)

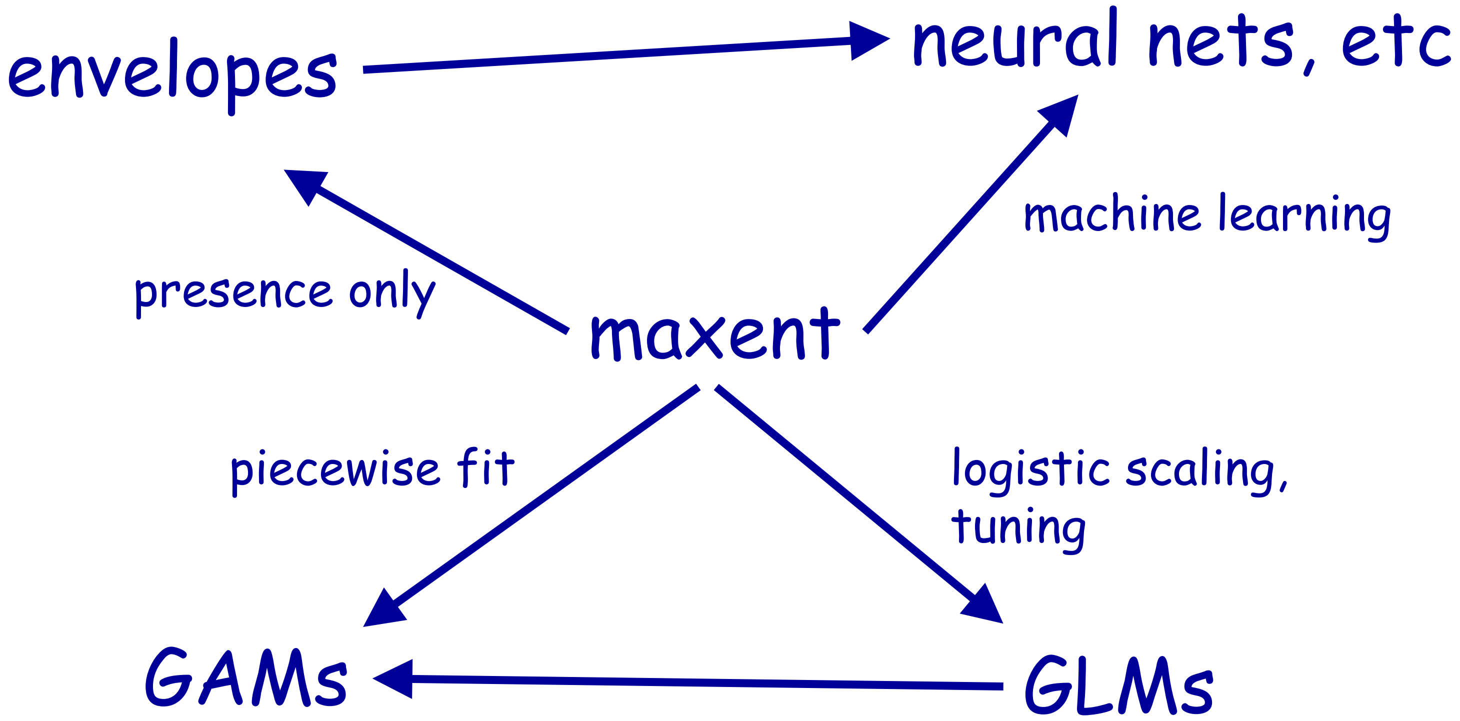
- Estimation via maximum entropy:
  - Fitted distribution (the “model”) should be consistent with the data but not assume anything beyond this
  - Fit is to minimize distributional difference between the presences and the background of what is available
  - Solution is machine-learning

Maxent: interpretation

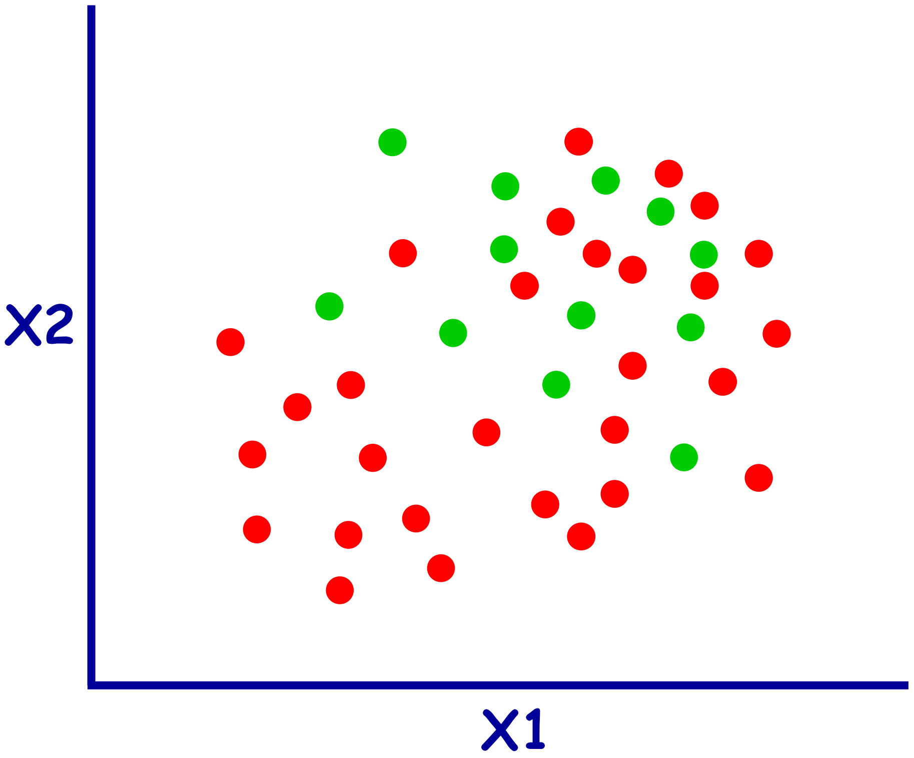
The maxent software package:

- Presence-only model (not really)
- *A* machine-learning solution
- *A* user-friendly interface (!)
  - Optimize true positives vs area
  - Tuning possible
  - Rescaled to look like a GLM
  - *Lots* of interpretative aids!

Models: connections



Statistics: Applications



- *Generative* models (envelopes, maxent) often perform better than *discriminative* models for rare species
- Models with flexible fits (CART, maxent) often perform better than global, linear models

Statistical models: reminders

- In ecological applications, models often perform very differently
  - Try a few models and compare/average
- The statistical tools are blind to ecology:
  - Implications of assumptions often must be accounted in model interpretation