

Bayesian model uncertainty

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hurricane Joaquin



model uncertainty

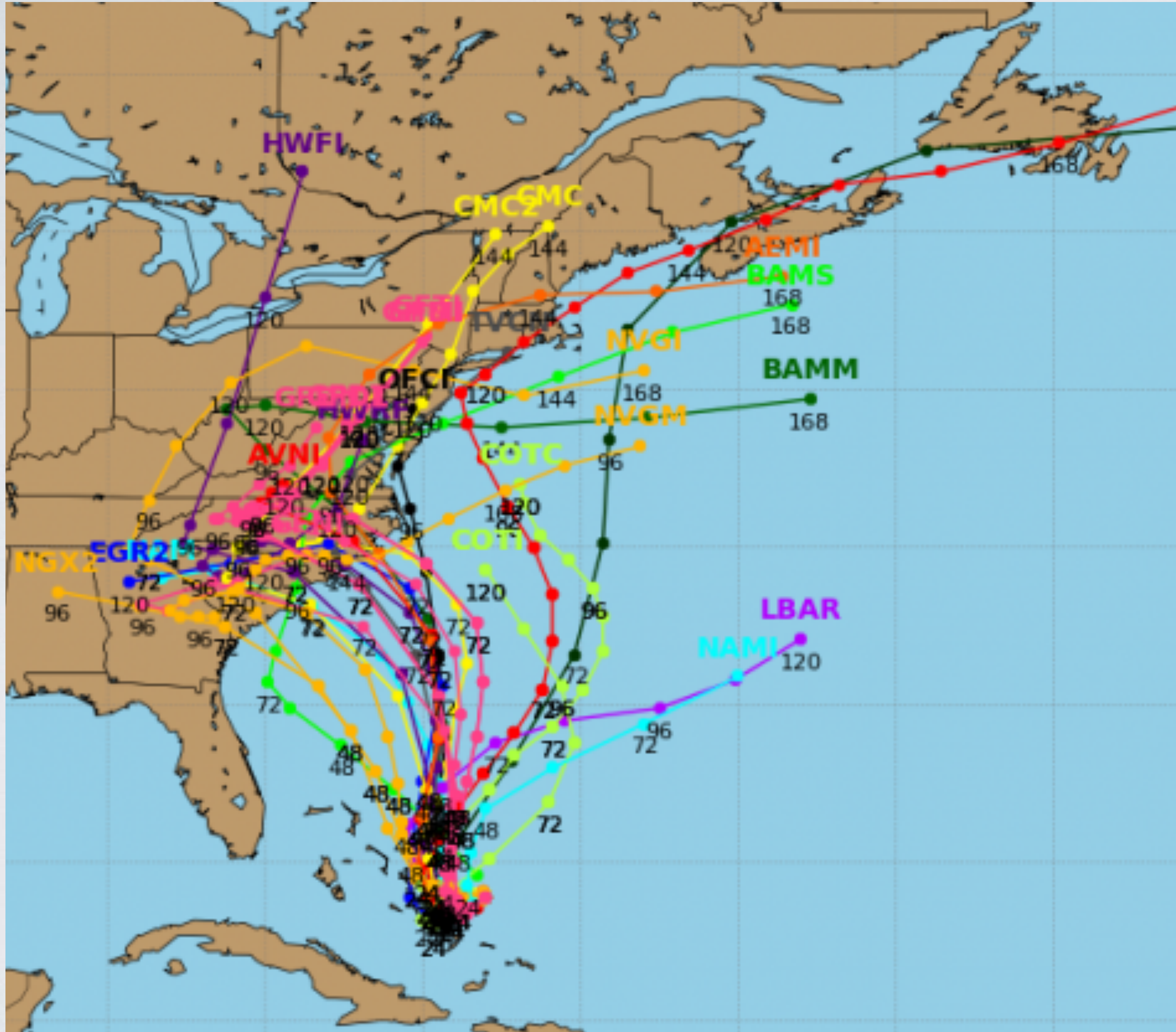


Image from Levi Cowan, <http://tropicaltidbits.com>

posterior model probabilities

- ▶ assign each model a prior probability $p(\mathcal{M}_m)$
- ▶ Bayes theorem \Rightarrow posterior model probabilities

$$p(\mathcal{M}_m \mid \text{data}) = \frac{\text{marginal likelihood of model } \mathcal{M}_m \times p(\mathcal{M}_m)}{\sum_{j=1}^{2^p} \text{marginal likelihood of model } \mathcal{M}_j \times p(\mathcal{M}_j)}$$

$$= \frac{\text{BF}[\mathcal{M}_m : \mathcal{M}_b] O[\mathcal{M}_m : \mathcal{M}_b]}{\sum_{j=1}^{2^p} \text{BF}[\mathcal{M}_j : \mathcal{M}_b] O[\mathcal{M}_j : \mathcal{M}_b]}$$

$$\text{BF}[\mathcal{M}_m : \mathcal{M}_b] = \frac{\text{marginal likelihood of model } \mathcal{M}_m}{\text{marginal likelihood of model } \mathcal{M}_b}$$

$$O[\mathcal{M}_m : \mathcal{M}_b] = \frac{p(\mathcal{M}_m)}{p(\mathcal{M}_b)}$$

R: posterior probabilities of all models

R

```
> library(BAS)
> cog_bas = bas.lm(kid_score ~ hs+iq+work+age,
+                  prior = "BIC",
+                  modelprior = uniform(),
+                  data = cognitive)
```

- ▶ base model intercept only
- ▶ $\text{BF}[\mathcal{M}_m : \mathcal{M}_1] = (1 - R_m^2)^{-n/2} \times n^{-p_m/2}$
- ▶ $p(\mathcal{M}_m) = \frac{1}{16} \Leftrightarrow O[\mathcal{M}_m : \mathcal{M}_1] = 1$

summary of top models

R

```
> round(summary(cog_bas), 3)
```

	Intercept	hs	iq	work	age	BF	PostProbs	R2	dim	logmarg
[1,]	1	1	1	0	0	1.000	0.529	0.214	3	-2583.135
[2,]	1	0	1	0	0	0.562	0.297	0.201	2	-2583.712
[3,]	1	0	1	1	0	0.109	0.058	0.206	3	-2585.349
[4,]	1	1	1	1	0	0.088	0.046	0.216	4	-2585.570
[5,]	1	1	1	0	1	0.061	0.032	0.215	4	-2585.939

- ▶ BIC is proportional to $-2 \times \text{logmarg}$
- ▶ base model for BF is best BIC model

83%

summary

- ▶ posterior probabilities on models
- ▶ BIC
- ▶ software

next:

- ▶ visualization
- ▶ Bayesian model averaging