Basic Verification Concepts

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Basic concepts - outline

- What is verification?
- Why verify?
- Identifying verification goals
- Forecast “goodness”
- Designing a verification study
- Types of forecasts and observations
- Matching forecasts and observations
- Statistical basis for verification
- Comparison and inference
- Verification attributes
- Miscellaneous issues

What is verification?

- Verify: **ver·i·fy**
  Pronunciation: 'ver-&-"fI
  1 : to confirm or substantiate in law by oath
  2 : to establish the truth, accuracy, or reality of <*verify* the claim>
  synonym see CONFIRM

- Verification is the process of comparing forecasts to relevant observations
  - Verification is one aspect of measuring forecast ***goodness***

- Verification measures the ***quality*** of forecasts (as opposed to their ***value***)

Why verify?

- Purposes for verification (traditional definition)
  - Administrative
  - Scientific
  - Economic

Why verify?

- Administrative purpose
  - Monitoring performance
  - Choice of model or model configuration (has the model improved?)
- Scientific purpose
  - Identifying and correcting model flaws
  - Forecast improvement
- Economic purpose
  - Improved decision making
  - “Feeding” decision models or decision support systems

Why verify?

- What are some other reasons to verify hydrometeorological forecasts?

Why verify?

- What are some other reasons to verify hydrometeorological forecasts?
  - Help operational forecasters understand model biases and select models for use in different conditions
  - Help “users” interpret forecasts (e.g., “What does a temperature forecast of 0 degrees really mean?”)
  - Identify forecast weaknesses, strengths, differences

Identifying verification goals

- What *questions* do we want to answer?
  - Examples:
    - In what locations does the model have the best performance?
    - Are there regimes in which the forecasts are better or worse?
    - Is the probability forecast well calibrated (i.e., reliable)?
    - Do the forecasts correctly capture the natural variability of the weather?

Other examples?

Identifying verification goals (cont.)

- What forecast performance ***attribute*** should be measured?
  - Related to the *question* as well as the type of forecast and observation
- Choices of verification statistics/measures/graphics
  - Should match the type of forecast and the attribute of interest
  - Should measure the quantity of interest (i.e., the quantity represented in the question)

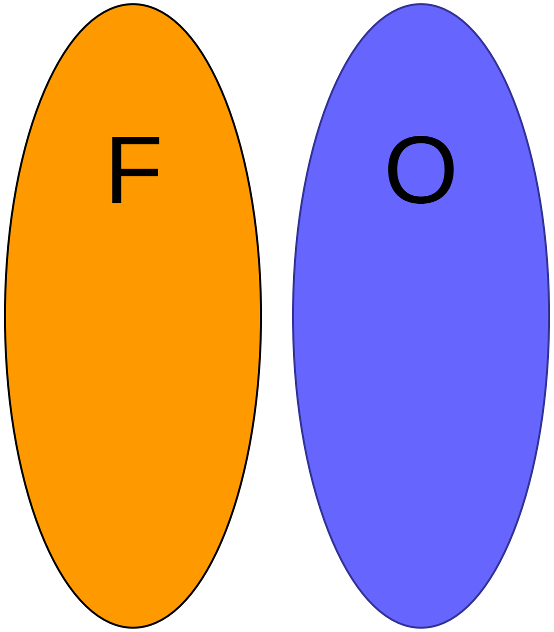
Forecast "goodness"

- Depends on the quality of the forecast

AND

- The user and his/her application of the forecast information

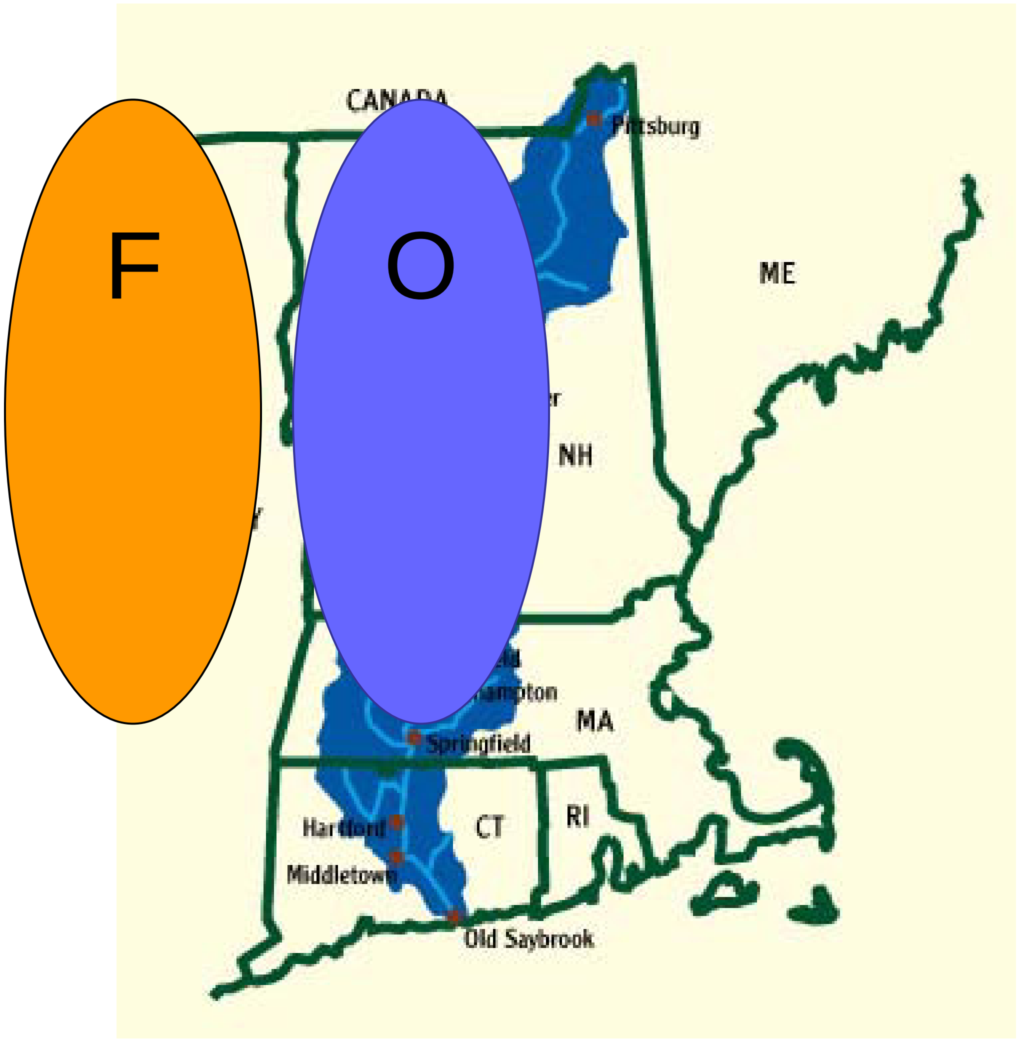
Good forecast or bad forecast?



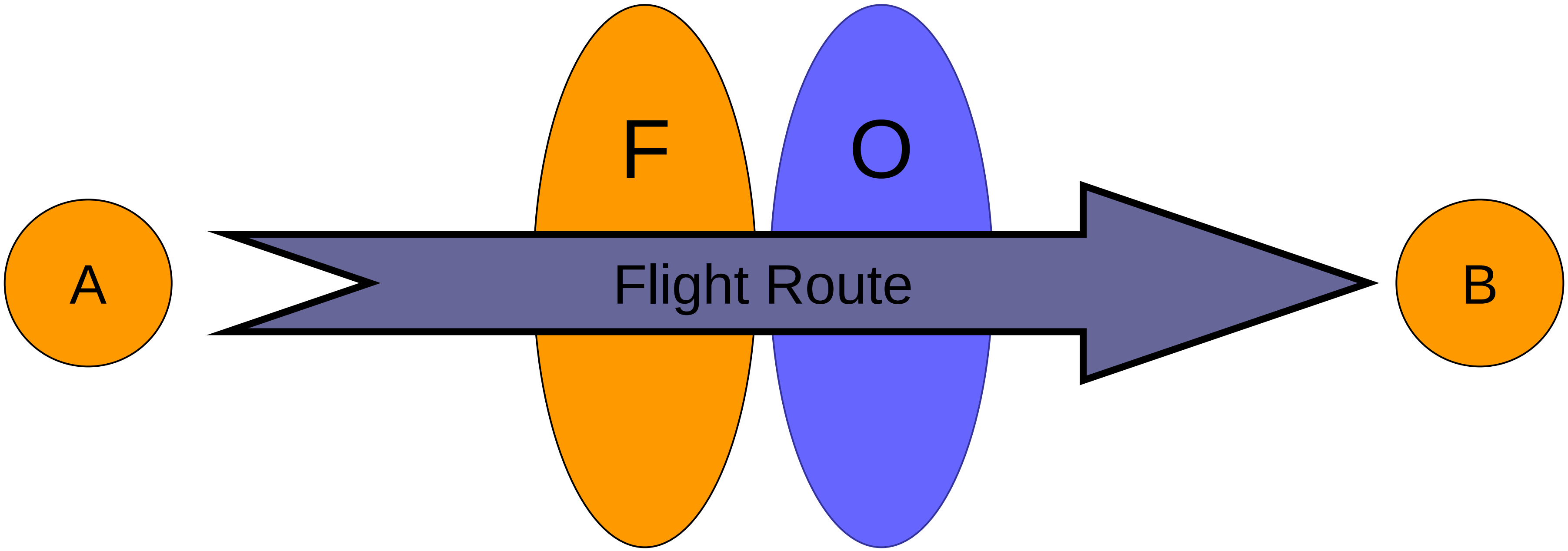
Many verification approaches would say that this forecast has NO skill and is very inaccurate.

Good forecast or Bad forecast?

If I'm a water manager for this watershed, it's a pretty bad forecast…



Good forecast or Bad forecast?



If I'm an aviation traffic strategic planner…

It might be a pretty good forecast

Different users have different ideas about what makes a forecast good

Different verification approaches can measure different types of "goodness"

Forecast "goodness"

- Forecast quality is only one aspect of forecast "goodness"
- Forecast value is related to forecast quality through complex, non-linear relationships
  - In some cases, *improvements in forecast quality (according to certain measures) may result in a* *<u>degradation</u>* *in forecast value for some users!*
- ***However*** - Some approaches to measuring forecast quality can help understand goodness
  - Examples
    - Diagnostic verification approaches
    - New features-based approaches
    - Use of multiple measures to represent more than one attribute of forecast performance

Simple guide for developing verification studies

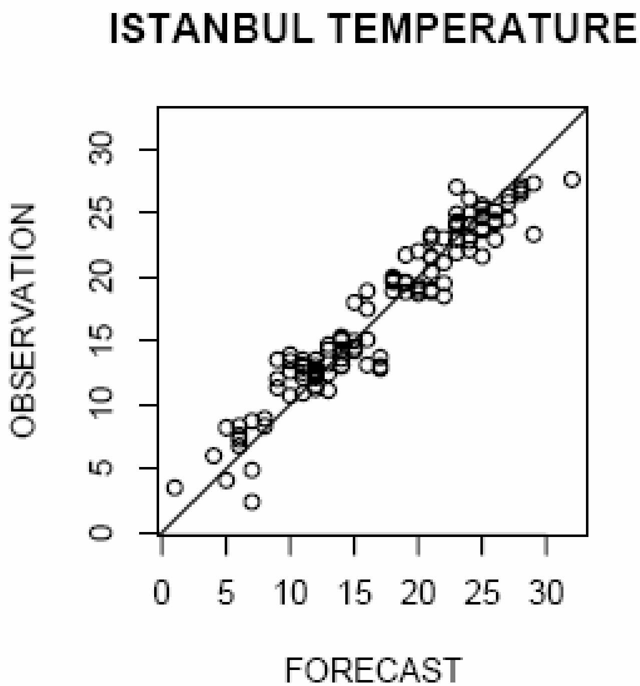
- Consider the users...
  - ... of the forecasts
  - ... of the verification information
- What aspects of forecast quality are of interest for the user?
- Develop verification questions to evaluate those aspects/attributes
- *Exercise*: What verification questions and attributes would be of interest to ...
  - ... operators of an electric utility?
  - ... a city emergency manager?
  - ... a mesoscale model developer?

Simple guide for developing verification studies

- Identify observations that represent the *event* being forecast, including the
  - Element (e.g., temperature, precipitation)
  - Temporal resolution
  - Spatial resolution and representation
  - Thresholds, categories, etc.
- Identify multiple *verification attributes* that can provide answers to the questions of interest
- Select *measures and graphics* that appropriately measure and represent the attributes of interest
- Identify a *standard of comparison* that provides a reference level of skill (e.g., persistence, climatology, old model)

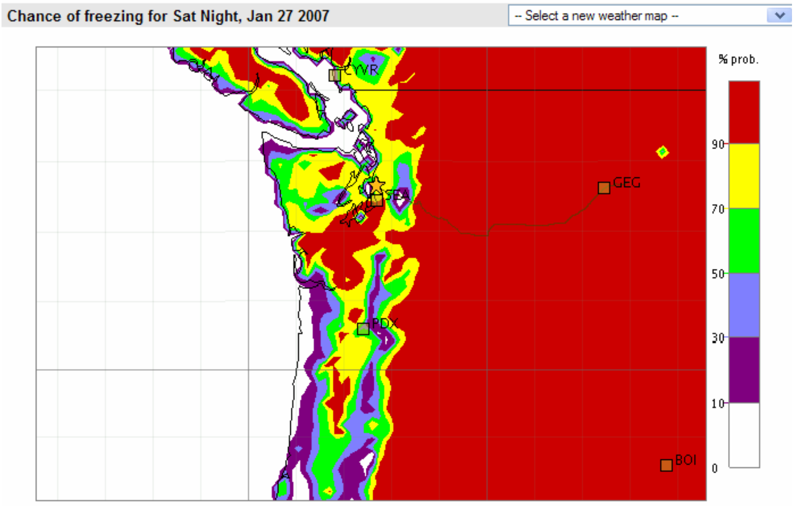
Types of forecasts, observations

- Continuous
  - Temperature
  - Rainfall amount
  - 500 mb height
- Categorical
  - Dichotomous
    - Rain vs. no rain
    - Strong winds vs. no strong wind
    - Night frost vs. no frost
    - Often formulated as Yes/No
  - Multi-category
    - Cloud amount category
    - Precipitation type
  - May result from *subsetting* continuous variables into categories



Types of forecasts, observations

- Probabilistic
  - Observation can be dichotomous, multi-category, or continuous
    - Precipitation occurrence – Yes/No
    - Precipitation type
    - Temperature distribution
  - Forecast can be
    - Single probability value (for dichotomous events)
    - Multiple probabilities (discrete probability distribution for multiple categories)
    - Continuous distribution
  - For dichotomous or multiple categories, probability values may be limited to certain values (e.g., multiples of 0.1)



Probability of freezing temperatures; from U. Washington

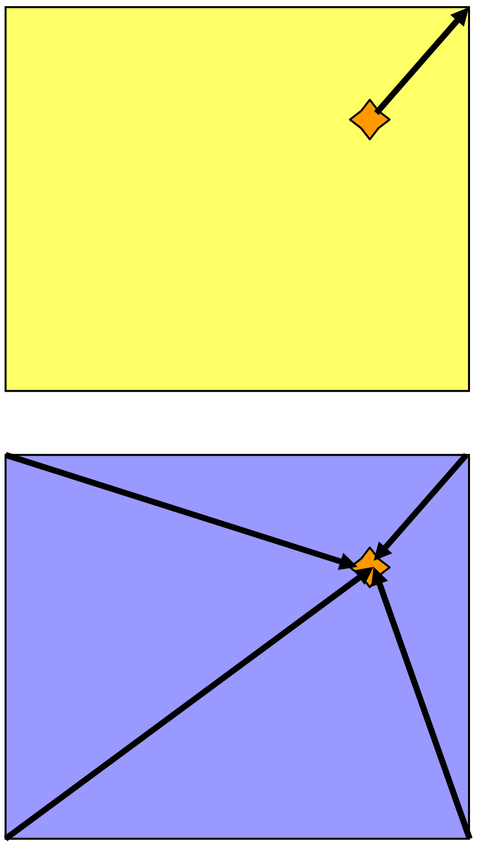
- Ensemble
  - Multiple iterations of a continuous or categorical forecast
    - May be transformed into a probability distribution
  - Observations may be continuous, dichotomous or multi-category

Matching forecasts and observations

- May be the *most difficult* part of the verification process!
- Many factors need to be taken into account
  - Identifying observations that represent the forecast event
    - Example: Precipitation accumulation over an hour at a point
  - For a gridded forecast there are many options for the matching process
    - Point-to-grid
      - Match obs to closest gridpoint
    - Grid-to-point
      - Interpolate?
      - Take largest value?

Matching forecasts and observations

- Point-to-Grid and Grid-to-Point
- Matching approach can impact the results of the verification

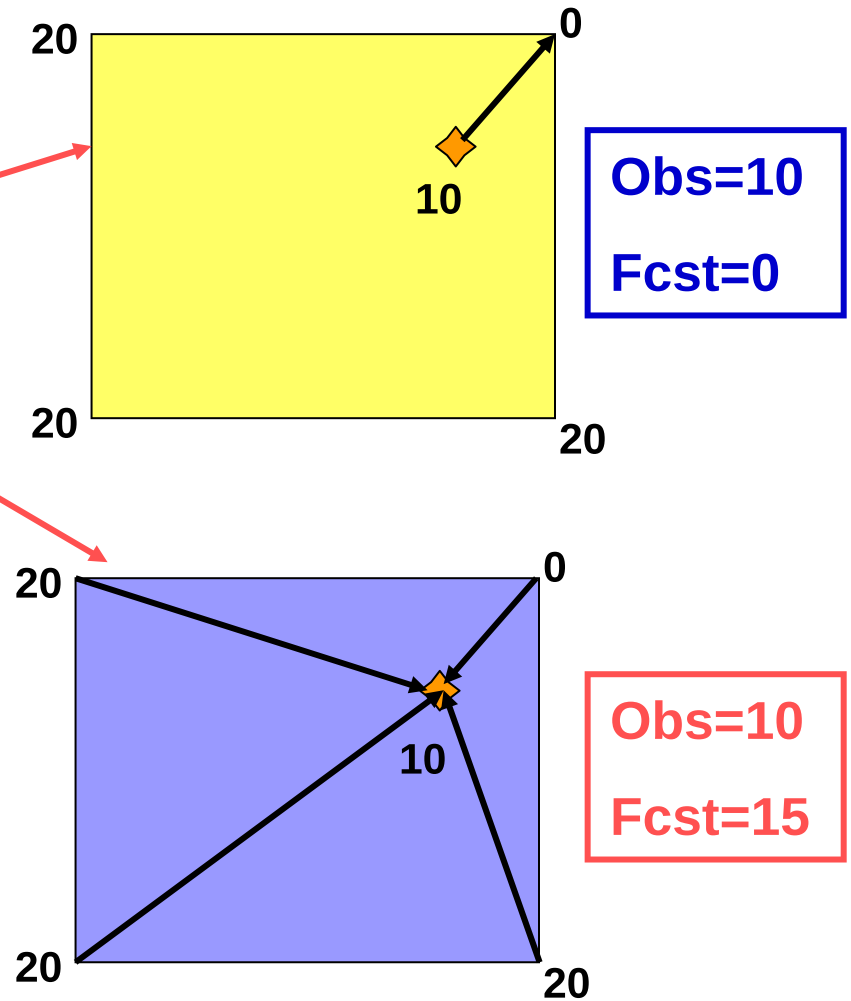


Matching forecasts and observations

<u>Example:</u>

- Two approaches:
  - Match rain gauge to nearest gridpoint ***or***
  - Interpolate grid values to rain gauge location
    - Crude assumption: equal weight to each gridpoint
- Differences in results associated with matching:

  "representativeness" error



Matching forecasts and observations

Final point:

- It is not advisable to use the model analysis as the verification “observation”
- Why not??

Matching forecasts and observations

<u>Final point:</u>

- It is not advisable to use the model analysis as the verification "observation"
- Why not??
- Issue: Non-independence!!

Statistical basis for verification

- Joint, marginal, and conditional distributions are useful for understanding the statistical basis for forecast verification

    - These distributions can be related to specific summary and performance measures used in verification

    - Specific attributes of interest for verification are measured by these distributions

Statistical basis for verification

- Basic (marginal) probability

$$p_x = \Pr(X = x)$$

is the probability that a random variable, X, will take on the value x

<u>Example</u>:

- *X = gender of tutorial lecturer*
- *What is an estimate of* $\mathbf{Pr(}\boldsymbol{X=female}\mathbf{)}$ *?*

Statistical basis for verification

- Basic (marginal) probability

$$p_x = \Pr(X = x)$$

is the probability that a random variable, X, will take on the value x

Example:

- X = *gender of tutorial lecturer*
- *What is an estimate of* $\mathbf{Pr(}\boldsymbol{X}\mathbf{=}\boldsymbol{female}\mathbf{)}$ *?*
- Answer:
  - Female lecturers (3): B. Brown, B. Casati, E. Ebert
  - Male lecturers (4): S. Mason, P. Nurmi, M. Pocernich, L. Wilson
  - Total number of lecturers: 7

$\mathbf{Pr(}\boldsymbol{X}\mathbf{=}\boldsymbol{female}\mathbf{)}$ is 3/7 = 0.43

Basic probability

- Joint probability

$$p_{x,y} = \Pr(X = x, Y = y)$$

= probability that both events x and y occur

  - Example: What is the probability that a lecturer is female and has dark hair?

Basic probability

- Joint probability

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  - Example: What is the probability that a lecturer is female and has dark hair?
    - Answer:

      3 of 7 lecturers are female

      2 of the 3 female lecturers have dark hair

      Thus, the probability that a lecturer is female and has dark hair is

$$\Pr(X = female, Y = dark\,hair) = \frac{2}{7}$$

where X is gender and Y is hair color

Basic probability

- Conditional probability

$$\Pr(X = x \mid Y = y) \quad \text{or} \quad \Pr(Y = y \mid X = x)$$

  - Probability associated with one attribute – given the value of a second attribute
  - Example
    - What is the probability that hair color is dark, given a lecturer is female?

$$\Pr(Y = \textit{dark hair} \mid X = \textit{female})$$

    - What is the probability that a lecturer is male, given hair color is dark?

$$\Pr(X = \textit{male} \mid Y = \textit{dark hair})$$

(Note: “Gray” counts as “light” ☺)

What does this have to do with verification?

- Verification can be represented as the process of evaluating the joint distribution of forecasts and observations, $p(f,x)$
  - All of the information regarding the forecast, observations, and their relationship is represented by this distribution
  - Furthermore, the joint distribution can be factored into two pairs of conditional and marginal distributions:

$$p(f,x) = p(F=f \mid X=x)\,p(X=x)$$

$$p(f,x) = p(X=x \mid F=f)\,p(F=f)$$

Decompositions of the joint distribution

- Many forecast verification attributes can be derived from the conditional and marginal distributions
- Likelihood-base rate decomposition

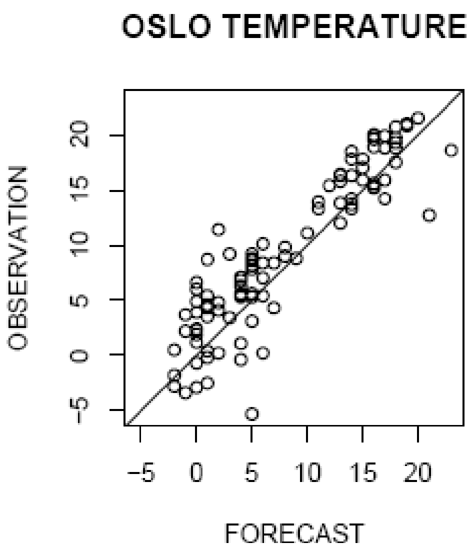
$$p(f,x) = \underbrace{p(F=f \mid X=x)}_{\text{Likelihood}}\,\underbrace{p(X=x)}_{\text{Base rate}}$$

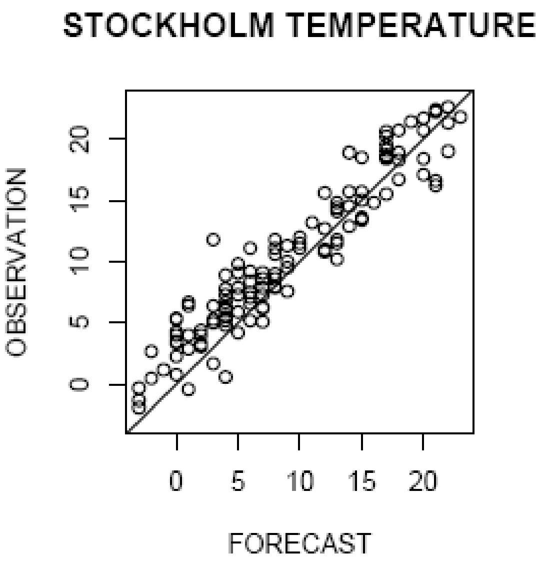
- Calibration-refinement decomposition

$$p(f,x) = \underbrace{p(X=x \mid F=f)}_{\text{Calibration}}\,\underbrace{p(F=f)}_{\text{Refinement}}$$

Graphical representation of distributions

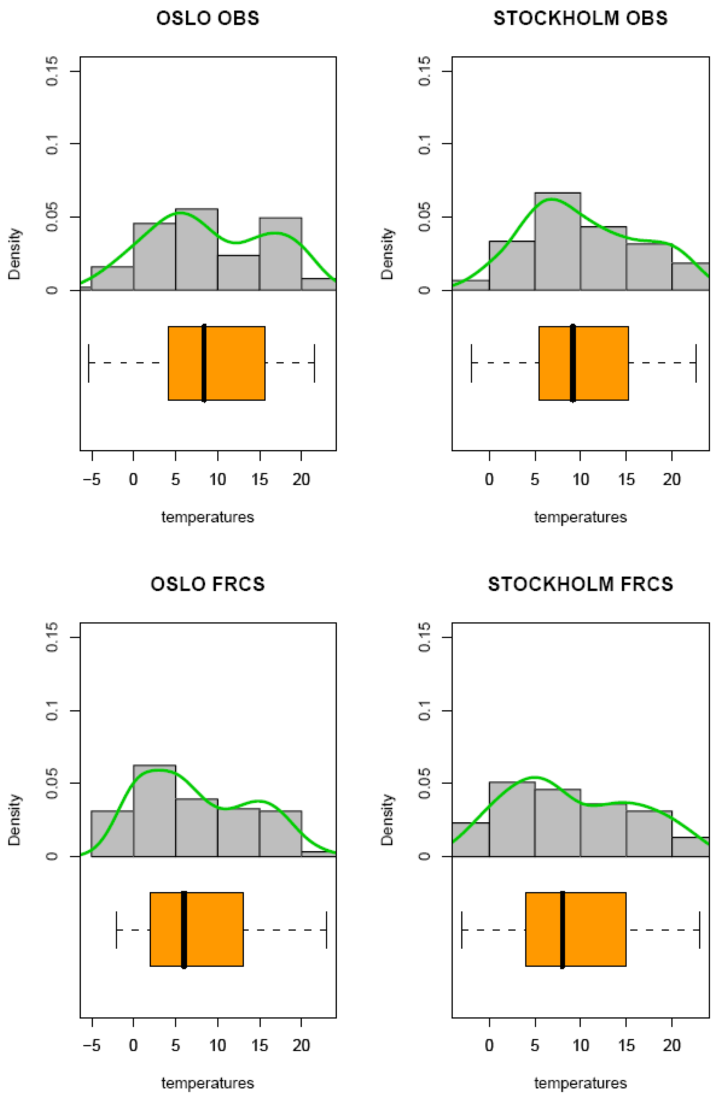
- Joint distributions
  - Scatter plots
  - Density plots
  - 3-D histograms
  - Contour plots





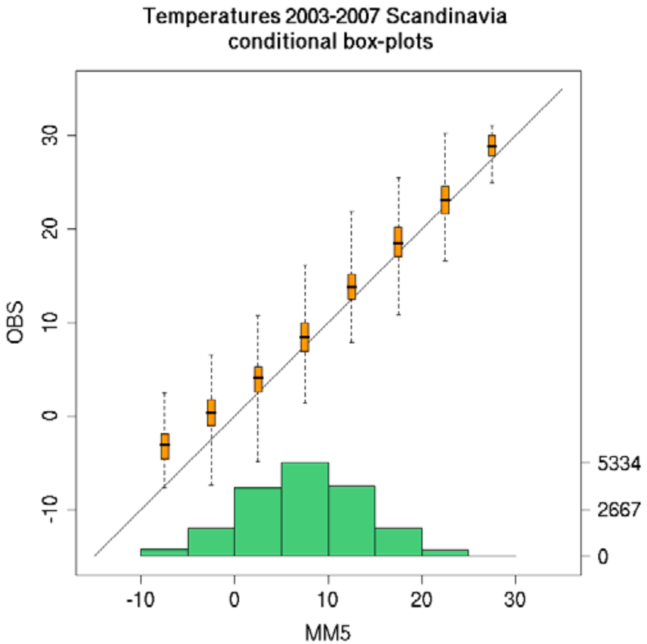
Graphical representation of distributions

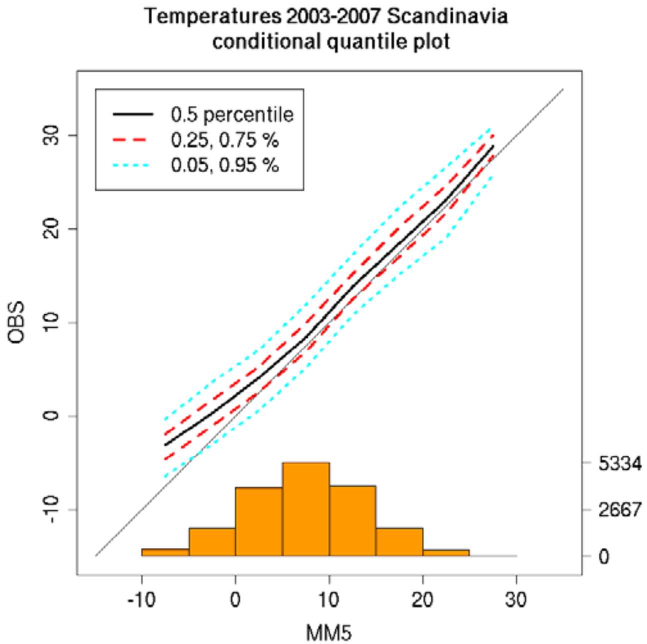
- Marginal distributions
  - Stem and leaf plots
  - Histograms
  - Box plots
  - Cumulative distributions
  - Quantile-Quantile plots



Graphical representation of distributions

- Conditional distributions
  - Stem and leaf plots
  - Conditional quantile plots
  - Conditional boxplots





Exercise: Stem and leaf plots

Probability forecasts (Tampere)

Date 2003	Observed rain??	Forecast (probability)
Jan 1	No	0.3
Jan 2	No	0.1
Jan 3	No	0.1
Jan 4	No	0.2
Jan 5	No	0.2
Jan 6	No	0.1
Jan 7	Yes	0.4
Jan 8	Yes	0.7
Jan9	Yes	0.7
Jan 12	No	0.2
Jan 13	Yes	0.2
Jan 14	Yes	1.0
Jan 15	Yes	0.7

Stem and leaf plots: Marginal and conditional

Marginal distribution of Tampere probability forecasts

	Forecast probability			
0.0				
0.1				
0.2				
0.3				
0.4				
0.5				
0.6				
0.7				
0.8				
0.9				
1.0				

Conditional distributions of Tampere probability forecasts

Obs precip = No					Obs precip = Yes			
				0.0				
				0.1				
				0.2				
				0.3				
				0.4				
				0.5				
				0.6				
				0.7				
				0.8				
				0.9				
				1.0				

Instructions: Mark X's in the appropriate cells, representing the forecast probability values for Tampere.

The resulting plots are one simple way to look at marginal and conditional distributions.

R exercise: Representation of distributions

Comparison and inference

- Skill scores
  - A skill score is a measure of *relative performance*
    - *Ex: How much more accurate are Laurie Wilson's temperature predictions than climatology (or my temperature predictions)?*
    - *Provides a comparison to a* ***standard***
  - Generic skill score definition

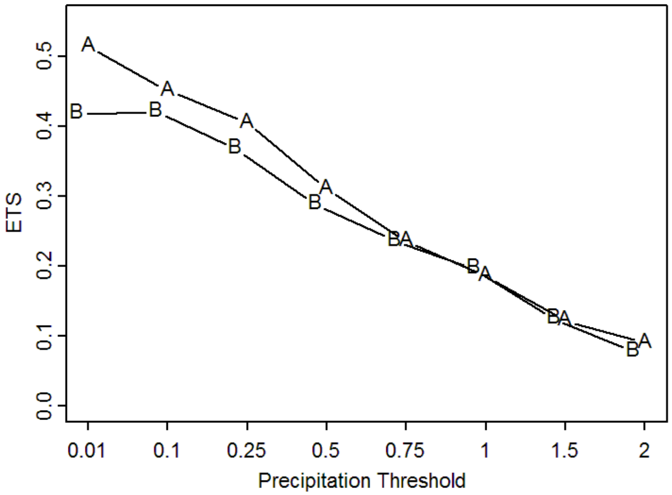
$$\frac{M - M_{ref}}{M_{perf} - M_{ref}}$$

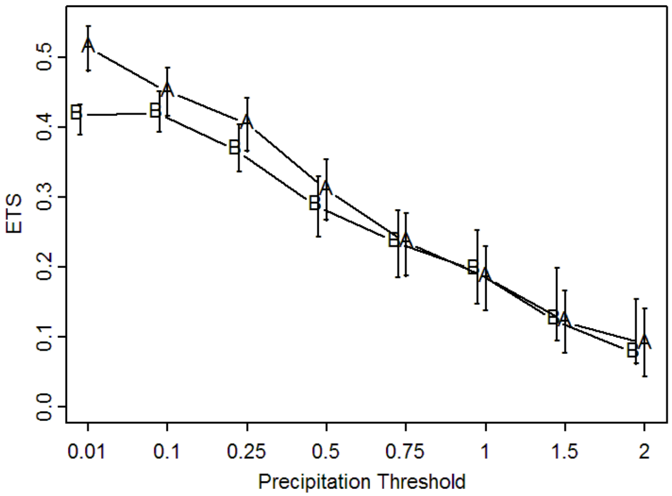
Where M is the verification measure for the forecasts, M_{ref} is the measure for the reference forecasts, and M_{perf} is the measure for perfect forecasts

  - Positively oriented (larger is better)

Comparison and inference

- Uncertainty in scores and measures should be estimated whenever possible!
  - Uncertainty arises from
    - Sampling variability
    - Observation error
    - Representativeness error
    - Others?
  - Erroneous conclusions can be drawn regarding improvements in forecasting systems and models
  - Confidence intervals and hypothesi tests
    - Parametric (i.e., depending on a statistical model)
    - Non-parametric (e.g., derived from re-sampling procedures, often calle "bootstrapping")





Verification attributes

- Verification attributes measure different aspects of forecast quality
  - Represent a range of characteristics that should be considered
  - Many can be related to joint, conditional, and marginal distributions of forecasts and observations

Verification attribute examples

- Bias
  - (Marginal distributions)
- Correlation
  - Overall association (Joint distribution)
- Accuracy
  - Differences (Joint distribution)
- Calibration
  - Measures conditional bias (Conditional distributions)
- Discrimination
  - Degree to which forecasts discriminate between different observations (Conditional distribution)

Desirable characteristics of verification measures

- Statistical validity
- Properness (probability forecasts)
  - "Best" score is achieved when forecast is consistent with forecaster's best judgments
  - "Hedging" is penalized
  - Example: Brier score
- Equitability
  - Constant and random forecasts should receive the same score
  - Example: Gilbert skill score (2x2 case); Gerrity score
  - No scores achieve this in a more rigorous sense
    - Ex: Most scores are sensitive to bias, event frequency

Miscellaneous issues

- In order to be *verified*, forecasts must be formulated so that they are *verifiable*!
  - Corollary: All forecast should be verified – if something is worth forecasting, it is worth verifying
- Stratification and aggregation
  - Aggregation can help increase sample sizes and statistical robustness but can also hide important aspects of performance
    - Most common regime may dominate results, mask variations in performance
  - Thus it is very important to *stratify results into meaningful, homogeneous sub-groups*

Verification issues cont.

- Observations
  - No such thing as “truth”!!
  - Observations generally are more “true” than a model analysis (at least they are relatively more independent)
  - Observational uncertainty should be taken into account in whatever way possible
    - e.g., how well do adjacent observations match each other?

Stem and leaf plots: Marginal and conditional

Marginal distribution of Tampere probability forecasts

	Forecast probability			
0.0				
0.1	X	X	X	
0.2	X	X	X	X
0.3	X			
0.4	X			
0.5				
0.6				
0.7	X	X	X	
0.8				
0.9				
1.0	X			

Conditional distributions of Tampere probability forecasts

Obs precip = No					Obs precip = Yes			
				0.0				
	X	X	X	0.1				
	X	X	X	0.2	X			
			X	0.3				
				0.4	X			
				0.5				
				0.6				
				0.7	X	X	X	
				0.8				
				0.9				
				1.0	X			