M ET3220C ComputationalStatistics

Forecast V erification

(Chapter 7 of Wilk's book)

Key Points: 1) Background on term inology 2) Contingency tables 3) Quantitative measures of skill.

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From A Seem ingly Backward Perspective

- Recall that the joint distribution of forecasts and observations • $p(y_i, o_i) = Pr(y_i, o_i) = Pr(y_i \cap o_i)$; for i = 1 to I; j = 1 to J
- From the perspective of som eone applying a forecast, the above equation can be refined as $p(y_i o_i) = p(y_i b_i) p(o_i)$.
- That is the likelihood of a certain forecast value, given a particular observation. This is called the likelihood-base rate factorization (Mumphy and Winkler 1987)

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Forecast V exification

Forecast Skill

- There are many measures of forecast skill.
- D ifferent m easures em phasize different strengths and w eaknesses.
- One of the most common measures is a 'skill score."

$$SS_{ref} = \frac{A - A_{ref}}{A_{perf} - A_{ref}} \times 100\%$$

- Where
 - A is a measure of accuracy,
 - $\bullet~\text{A}_{\text{perf}}$ is a the m easure of accuracy for a perfect forecast, and
 - \bullet $\mathbf{A}_{\mathrm{nef}}$ is reference level to which the accuracy is compared.
- If A < A_{xef}, then the skill score is negative,
 - If $A = A_{ref}$, then the skill score is zero,
 - If A_{perf} > A > A_{ref}, then the skill score is positive and less than 1,
 - If $A = A_{perf}$, then the skill score is one.
- $A_{\rm ref}$ is often set to the accuracy of a forecast based solely on clim atology.

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Forecast V enification

Joint Distributions

of Forecasts and O bservations

- Consider a forecasty, with I possible values or bins of values.
 - Values orbins are y₁, y₂, y₃,..., y₁
- Consider the corresponding observation o, with J possible values or bins of values.
- Values orbins are $o_1, o_2, o_3, \dots, o_J$
- The 'pint distribution of forecasts and observations is written as
 - $p(y_i o_i) = Pr(y_i o_i) = Pr(y_i \cap o_i)$; for i = 1 to I; j = 1 to J
 - This function associates a probability with each of the possible $\mathbb{I} \times \mathbb{J}$ possible combinations of forecast and observation.
- From the perspective of someone attempting to calibrate (or tune) a forecast, the above equation can be refined as $p(y_i, o_j) = p(o_j|y_i) p(y_i)$.
- That is the likelihood of a certain observed value, given a particular forecast. This is called the calibration-refinement (M unphy and Winkler1987).

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Forecast V erification:

- How Many Data Do We Need?

 We need enough data to make an adequate estimation of the probability of each of the IxJ possible outcomes.
- Example:
 - A ssum e that we are rounding tem perature forecasts to the nearest. degree, and that there are 50 possible outcome for observations, and 60 possible outcomes for the forecast.
 - We then need a minimum of 50×60 times the number of observations needed to make an adequate estimation of a single probability. Why is this aminimum?
 - Recall that the numberneeded to determ ine a probability to within
 a specific measure of error is dependent on the probability.
 - We need to assume the worst in this calculation!
 - Say 1000 points.
 - Then we need 50×60 times 1000 observations = 3,000,000 observations.
 - Collected in a time and space where the statistics do not

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Contingency Tables

 M any m easures of skill (or lack of skill) can be described in term s of the odds of outcomes based on a 2x2 contingency table.

a + b

O bserved Condition

	Observed Condition			
		Y es	No	
Forecast Condition	Yes	н <u>і</u> і. (а)	False Alam (b)	
	No	Miss (c)	Connect: N egative (d)	
		a + c	b+d	

 The num bers outside the 2x2 box are the marginal totals.

- Bottom totals are the marginal totals of the observations.
- Left totals are the marginal. totals of the forecasts
- The sum of the marginal total for observations M UST equal the sum a+b+ of the marginal totals for the
- c + d = n forecasts. • Both sum s are equal to n.

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Contingency Tables for Probabilities

• A sim ilar 2x2 table can be constructed for probabilities of the ipint distribution.

Observed Condition Yes No Нit (a + b)/h A larm (a/h) (b/h) $= p(0_1)$ Correct M iss No (c + d)/hN egative (c/h) (d/h) (a + c)/h (b + d)/h $= p(y_2)$ $= p(y_1)$

- The numbers outside the 2x2 box are the marginal distributions.
 - · Bottom totals are the marginal distributions of the observations.
 - Left totals are the marginal distributions of the forecasts
- = $p(O_2)$ The sum of the marginal distributions for observations M UST equal the sum of the m arginal distributions for the forecasts.MUST equal1.

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Scalar Measure of Skill

Based on The Contingency Table

- M any of the following measures of skillwere first developed in m edical fields. Applied m edicine journals often provide m ore useful inform ation on the strengths and weaknesses of these techniques than can be found in meteorology discussions. A couracy
- - A couracy (PC; percentage correct) indicates the fraction of correct forecasts.
 - Correct forecasts are hits and correct negatives
 - These are converted to a fraction by totaling them , and dividing by the sample size.
 - PC = (a + d) / n
- W hat does the value 1 PC indicate?
- The fraction of wrong forecasts (false alarms and misses).
- PC values near 1 are good, and values near zero are poor. How ever, if the events being forecast are rare, then PC does not give a good indication of skill in achieving hits. W hy?
- Because all the weight is on connect negatives!

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Threat Score or Critical Success Index

- The critical success index (CSI) is more appropriate to use that the PC for situations $\ensuremath{\mathbf{w}}$ hen the event being forecast is rare.
 - O riginally proposed by G ilbert (1884). Called ratio of verification.
- The CSI does not consider the number of correct negatives. It compares the number of hits to the number of non-'connect negatives.'
 - CSI=a/(a+b+c)
- A value of zero is appallingly bad.
- A value of one is perfect.

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OddsRatio

- The odds ratio (θ) exam ines a ratio of odds. In this context, odds are defined as a probability to the compliment of that probability, $p \mathrel{/} (1-p)$.
 - See Stephenson (2000) for the first meteorological application.
- In this case, consider the odds of a hit given that the event does occur, divided by the odds of a false alarm given that the event does not occur.
 - That is a ratio of the
 - odds of a hitgiven that the event does occur: [a/(a+c)]/[1-a/(a+c)] = a/c to
 - odds of a false alarm given that the event does not occur: [b/(b+d)]/[1-b/(b+d)]=b/d
 - $\theta = (a/c) / (b/d) = ad/(bc)$
- This ratio is the product of correct forecasts to the product of incorrect forecasts
- A value of one is consistent with forecasts that are independent of observations. Larger is better.

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False Alarm Rate (FAR)

- The false alarm rate is the chance of false alarm given that the forecast event did not occur.
 - FAR = b / (a + b)
 - Smaller values are better.
- FAR is very in portant when the consequences of a false alarm are sembus
 - Example close schools and offices on the basis of a humicane forecast.

0 thers

- There are m any other skill scores.
- Wilks' text lists som e.
- On behalf of the the WWRP/WGNE Joint Working Group on V erification, the Australian Bureau of M eteorology web site lists many of those used in m eteorology, and has good explanations.
 - http://www.bom.gov.au/bmrc/wefor/s

• This web page is a good resource!

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