Tackling Concept Drift by Temp
Inductive Transfer

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Concept Drift

- Machine Learning
  - $h(X_0, X_1, X_2 \ldots X_n) = Y$
- Statistical relationship changes over time
  - $h(X_0, X_1, X_2 \ldots X_n)_t = Y_t$
  - $h(X_0, X_1, X_2 \ldots X_n)_{t+1} = Y_{t+1}$
  - $h(X_0, X_1, X_2 \ldots X_n)_{t+m} = Y_{t+m}$

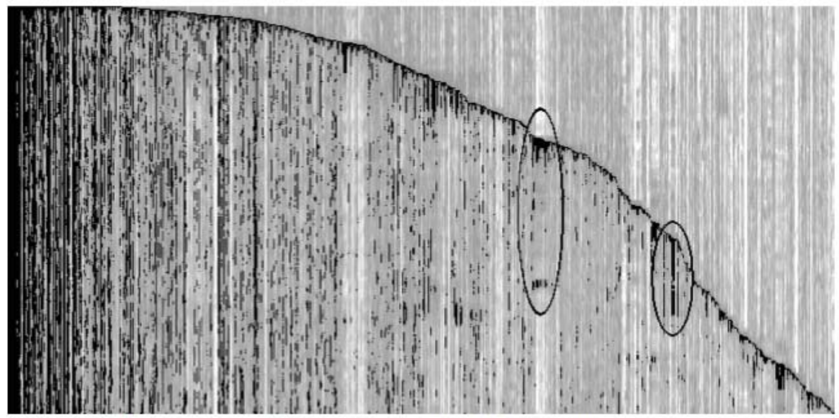
Concept Drift

- Class Distribution
  - Hepatitis A - Outbreaks occur with time invariant symptoms
- Subclass Distribution - Examined in Paper
  - Subclass distributions change
- Fickle Concept Drift
  - Cases may change ground truths over time - relevan

Daily Classification Task

- Time discretized into days
- 4 Binary Classification Tasks
  - Reuters RCV1
- Only use top 100 words for each day
  - Bi-Normal Separation
    - Like Information Gain

FxTime Visual Analysis



Category GCAT (government & social issues, 30%): 729 top predictive words

Temporal Inductive Transfe

- Use learned models from the past
- Augment with P binary features
  - What would P past models predict for today?
- Recurrence relation broken in this paper
  - Only use yesterday's model (which intrinsically uses
  - Hence, only one P value {0,1}

Temporal Inductive Transfe

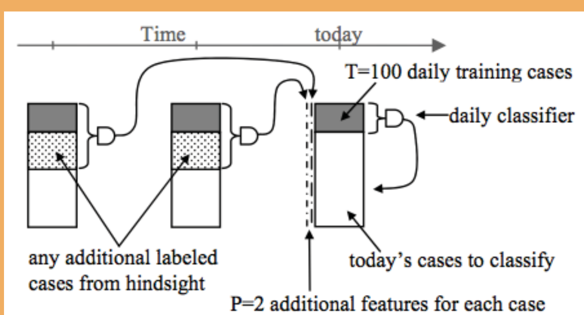
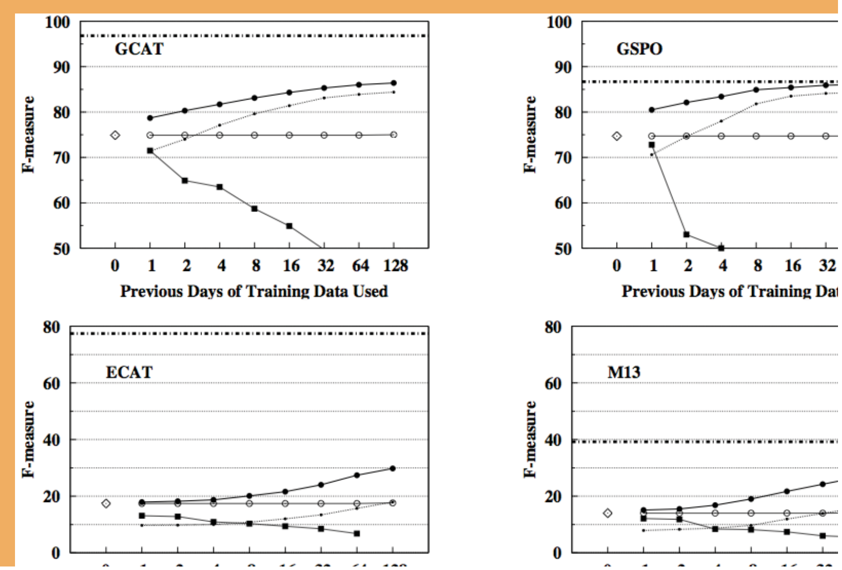
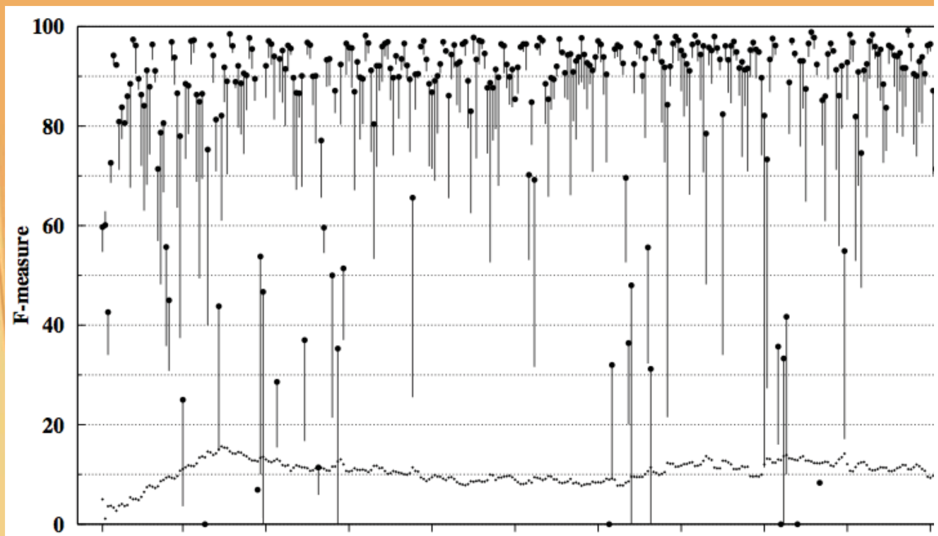


Figure 2. Temporal Inductive Transfer (TIX) Model

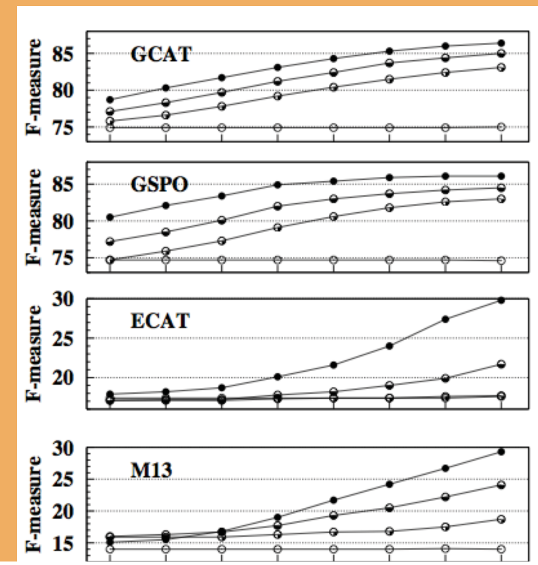
Results



Results



Results



Conclusions

- Effectively tackles concept drift
- Hindsight data required for Temporal Inducti
  Transfer to work
- Recurrence Chain Broken in tests
  - Future Work: increased accuracy if chain preserved
- Sliding window only useful in selective cases