Employing time-series forecasting to historical medical data: an application towards early prognosis within elderly health monitoring environments

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Seniors suffer from chronic diseases

Tele-health monitoring environments should be able to detect apart from rapid deterioration states or life-threatening situations also slow-varying health problems and provide early prognosis.

Cases such as the geriatric depression or cognitive decline are characterized by a gradual impairment that may last for years and will be hardly noticed by the seniors or their carers, except for late stages where the outcomes of the disease remain irreversible.
Goal

• Showcase:
  • the use of state-of-the-art machine learning and statistical methods
  • With a set of artificially developed scenarios, relevant to patient models with high risk of hypertension

• Our hypothesis is that one can take advantage of existing time-series forecasting methodologies to identify health trends over time and predict early signs of health deterioration, based on historical sets of health measurements and events
Time-series forecasting

• Pattern recognition of historical data
• Forecasting of future values based on historical trends
• State-of-the-art algorithms involve among others:
  • Exponential smoothing
  • Box-Jenkins seasonal ARIMA model
  • Artificial Neural Networks
  • Support Vector Machine
Materials & Methods

• Simulation of day-to-day blood pressure variation
• Blood pressure is a vital sign of crucial importance
• Uncontrolled blood pressure leads to conditions such as hypertension
• Abnormal blood pressure values (diastolic blood pressure > 90, systolic blood pressure > 140)
Materials & Methods

• Data set consists of:
  • Ten artificially generated cases, which reflect seniors at high risk
  • \( N \) (80, 1-3)
  • Based on a-priori knowledge, stemming from norms

• AI test bed
  • GaussianProcesses
  • SMOreg (Weka implementation of SVMs for time series forecasting)
  • MultilayerPerceptron
  • ARIMA statistical models
Experimentation

• Data sets split into half
  • Initial 50 instances were used as learning set, rest 50 instances as test set
  • Experimentation conditions:
    • Forecasting of future value ranges – lower, upper confidence intervals (ARIMA models)
    • Forecasting of future values (rest methods)
ARIMA forecasting performance

- Prediction accuracy → *correctly predicted instances of value range* / *total test instances*

- Average prediction accuracy → 91.2%

Forecast Range vs Actual Values of Diastolic Data (95% prediction intervals)

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# Results of single value forecasting

<table>
<thead>
<tr>
<th>Learning Method</th>
<th>Mean Absolute Error (MAE)</th>
<th>Root Mean Squared Error (RMSE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GaussianProcess</td>
<td>1.798633</td>
<td>2.292558</td>
</tr>
<tr>
<td>SVM</td>
<td>2.005342</td>
<td>2.523508</td>
</tr>
<tr>
<td>ANNs</td>
<td>6.061283</td>
<td>7.126667</td>
</tr>
</tbody>
</table>

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Discussion

- Medical time-series forecasting could have great impact on predicting future risky situations for health
- Box-Jenkins ARIMA models provide relatively accurate short-term forecasts in terms of value range
- SVMs and Gaussian Processes can provide relatively fair results predictions
Limitations

• Seniors tend to suffer from comorbidities, thus lots of factors influence their health status
• Currently, forecasting is applied to a single parameter
• A significant problem is the lack of data availability, due to sensor failures or seniors not adhere to the medical plan
Future plans

• Therefore there is a need for multifactorial analysis, multivariate time-series forecasting in order to investigate underlying temporal relationships with associative parameters
• Data imputation techniques can provide solution to the problem of missing data
• Lab and real-life testing are planned, some pre-pilots have already started
• Adaptive forecasting in terms of temporal window size, allowing experts to evaluate both short-term events and long-term future trends
Conclusion

• Medical time-series forecasting state-of-the-art methodologies could provide accurate predictions of future health states
• ARIMA models have been used for predicting future value confidence intervals
• SVMs, ANNs and Gaussian Processes also provide means of forecasting medical data
• Further analysis will be done with real-life data; several scenarios will be evaluated, e.g. vital signs monitoring for chronic conditions, cognitive decline and geriatric depression
Ambient Assisted Living environments

- Can we detect transition patterns indicative of future health deterioration?
- Can we timely estimate chronic alterations in the presence of outliers that may be either due to system (sensors) failure or to acute events?
- How can we act proactively and help seniors adopt a healthier lifestyle?

*Time-series forecasting when combined with other methodologies could provide solution to the above questions*
Section: Intelligence in Assistive Living

USEFIL
Unobtrusive Smart Environments For Independent Living

Contemporary Decision Support in Unobtrusive Environments. Issues, Methods, & USEFIL Advances

Prof. Panos Bamidis,
Lab of Medical Physics, Medical School, Aristotle University of Thessaloniki, GR
eHealth FORUM, Athens 13/05/2014

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Intelligent Health Monitoring challenges – the USEFIL approach

- In USEFIL we care about “unobtrusiveness”
- Decision Support (DSS) in USEFIL
  - pro-activeness
  - early detection of decline
  - disease prognosis
  - personalised guidance provision (adopting healthy lifestyle habits)
- Big challenges for AI & the evolving “smart” technologies
- Aim in USEFIL:
  - offer an arsenal of AI & statistics-based methods
  - ...in combination with off-the-shelf, low cost sensor monitoring &
  - ... new interaction devices
**Participant Characteristics:**
- Mood disorders
- Mobility problems
- Mild neuro-cognitive disorders
- Healthy seniors as controls

**Pilot Characteristics:**
- 4 weeks duration
- 3 sessions/week
- Appx. 1h session duration

**Data Acquisition:**
- Speech characteristics
- Activity recording & mobility pattern
- Physiological monitoring
- Cognitive/Physical training
- Mood profile & processing of emotional stimuli
- Interaction with end-users applications

**Experimental Condition:**
- Resting Condition
- Emotional stimulation
- Exercise

**Expected Outcome:**
- Algorithm testing
- Norms acquisition for HLE events
- Baseline extraction
Thank you!

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