Application of Bayesian Belief Network for Agile Kanban Backlog Estimation

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Application of Bayesian Belief Network for Agile Kanban Backlog Estimation

Abstract
Traditional Delivery Estimation • High level of maintenance • Difficult to predict lead times • New tasks added constantly • Tasks cancelled • Reprioritization • Current tools adapted to Agile Kanban

Disciplines
Industrial Engineering | Industrial Technology | Manufacturing | Other Operations Research, Systems Engineering and Industrial Engineering | Systems Engineering

Comments
This presentation is from Proceedings of the 2018 IISE Annual Conference held on May 19-22, 2018 at Orlando, Florida. Eric Weflen, Kevin Korniejczuk, Sharon Lau, Steve Kryk, Cameron MacKenzie, Iris V. Rivero Application of Bayesian Belief Network for Agile Kanban Backlog Estimation. Posted with permission.

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What is Agile Kanban? [1,2]

- Different from Kanban for JIT manufacturing!
- Visualization of workflow
- Limit work in process (WIP)

What is Agile Kanban?
Traditional Delivery Estimation

- Use “Story Point” estimation

  Brush Teeth  Breakfast  Run 5 mi

  0, 1, 2, 3, 5, 8, 13, 20, 50, 100

- Calculate Velocity (points/day)
- Use Velocity to estimate when task leave backlog

Traditional Delivery Estimation

• High level of maintenance
• Difficult to predict lead times
  • New tasks added constantly
  • Tasks cancelled
  • Reprioritization
• Current tools adapted to Agile Kanban
Bayesian Networks
(influence diagrams)

Graphical representation of a complex uncertainty

Decision → Uncertainty → Deterministic or Consequence
Research Question

Can a Bayesian Belief Network be used to estimate lead time for tasks to leave the backlog?
Model – Data Collection

- Need historical team data
- Tracked Kanban team at Andersen Crop.
- Team used Story Point estimation
- Collected data for 4 weeks
- Estimated conditional probabilities for 5 uncertainties
Decision – Backlog Position

- New project arrives
- Team needs to decide where in the ordered list the new project should be placed
- Alternatives: Position 5, 10, 15, 20, or 25
Backlog Position #5

- New Tasks Added
- Average Team Daily Velocity
- Tasks Canceled
- Reprioritized Backlog
- Average Backlog Item Size

Table: Days Until Work Starts on Task

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<th>Count</th>
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</table>

9.26 ± 4
Results - Cumulative Density Function

CDF: Lead Time

Probability Work Starts (%)

Lead Time (Business Days)

- Position 5
- Position 10
- Position 15
Conclusions

• Account for risks missed by story point estimation
• Reduce maintenance overhead
• Further work needed to verify accuracy