Towards Recommending Configurable Offerings

Juha Tiihonen[1],
Alexander Felfernig[2]

[1] Helsinki University of Technology
Department of Computer Science and Engineering

[2] University Klagenfurt
Intelligent Systems and Business Informatics

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Outline

- Motivation and background
- Recommendation scenarios
- Distance metrics
- Example: Most popular choice
- Discussion, future work and conclusions

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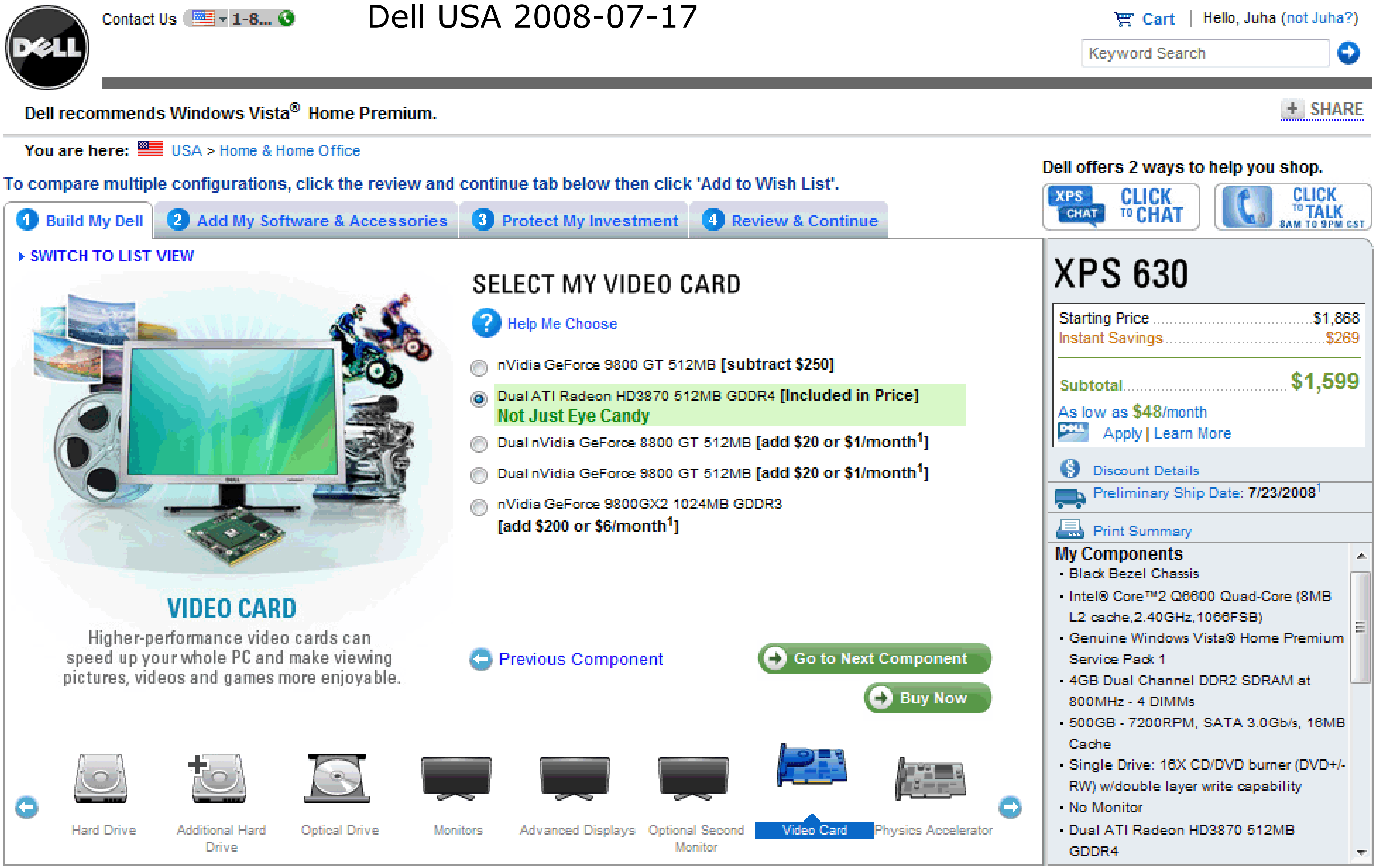

Motivation

- What of these configuration alternatives should I select? (Mass confusion)
  - "I want to edit high-definition videos, how to select components to my computer"
  - "Does this nVidia GeForce 9800 GT 512MB suit my requirements?"
- Preferences are constructed – which alternatives are presented to the customer, and their order highly affects the final selections
- Overlooking configuration alternatives which could better suit to the customers' wishes and needs

→ Users of configurators need more intuitive interaction mechanisms to select product and service alternatives

→ Integrate recommendation and configuration technologies

In this paper…

- Apply and extend case-based recommendation to configuration settings
- We extend previous recommendation approaches e.g. [Cöster et al.]
  - To take into account importance weights of features
  - To take into account similarity (substitutes equality)
  - To take consistency into account
    - generate only recommendations that are consistent with customer requirements and the configuration model
- In the paper we discuss ”Nearest neighbor”, ”Weighted Majority Voter”, “Most Popular Choice”
- Identify scenarios for recommendation supported configuration & discuss topics for future work

Recommendation scenarios

- Selecting a suitable base product line
- Recommending a complete configuration
- Recommending how to complete a configuration
- Recommending a subconfiguration
- Recommending individual attribute or component settings

→ a high diversity of usage and integration scenarios for recommendation technologies

Sample Configuration model & cases

Feature	Domain			
Video	no	sd	hd	
Photos	no	std	adv	
Gaming	2d	3d	adv	
PR	as	i4	i9	
mb	a1	a2	i1	i2
Ram	1	2	3	4
HD	h2	h5	h9	
GC	g2	g8	g9	-
OD	dr	dw	br	bw

k	f_1 **vi**	f_2 **ph**	f_3 **ga**	f_4 **pr**	f_5 **mb**	f_6 **me**	f_7 **hd**	f_8 **gc**	f_9 **od**	c
1	no	no	2d	as	a1	1	h2	no	dr	ba
2	no	std	2d	as	a2	1	h5	g2	dw	st
3	sd	std	adv	i4	i2	3	h5	g9	dw	ad
4	hd	adv	adv	i9	i2	4	h9	g9	bw	ad
5	sd	adv	3d	i4	i1	2	h9	g8	dw	st
u	no	no	3d							

$ph \neq no \implies od.dw = yes$: to archive photos
$ph = adv \implies hd.capacity \geq 500$: disk space for photos
$ph = adv \implies pr.CScr \geq 2500$: CPU for advanced photo

Other constraints in paper...

Distance metrics

- Distance functions determine similarity or dissimilarity of individual feature values
  - Traditional equality may be too strict - close values or configurations could remain ignored

$$d_{f_i}(x,y) = \begin{cases} 1 & \text{if x or y is unknown; otherwise} \\ vdm_{f_i}(x,y), & \text{if } f_i \text{ is symbolic} \\ diff_{f_i}(x,y), & \text{if } f_i \text{ is linear} \end{cases}$$

- Apply Heterogeneous Value Difference Metric (HVDM) [Wilson 1997]
  - Cope with symbolic (nominal) and numeric features
  - Learns the similarity of symbolic values in a domain automatically

$$\begin{aligned} vdm_{f_i}(x,y) &= \sqrt{\sum_{c=1}^{C} \left| \frac{N_{f_i,x,c}}{N_{f_i,x}} - \frac{N_{f_i,y,c}}{N_{f_i,y}} \right|^2} \\ &= \sqrt{\sum_{c=1}^{C} \left| P_{f_i,x,c} - P_{f_i,y,c} \right|^2} \end{aligned}$$

$$diff_{f_i}(x,y) = \frac{|x-y|}{4\sigma_{f_i}}$$

Most Popular Choice

- Recommends values for remaining features $\bar{F}_u$ from one configuration

Popularity of my (c) feature values in $\bar{F}_u$

Bayesian predictor for F_u to have current values given *Conf*

$$Pr(c, u, F_u) = Pr_{basic}(c, \bar{F_u}) * \prod_{j \in F_u} Pr(f_{j,u} = f_{j,u} | Conf)$$

- Extended Pr_{basic} from that presented in [Cöster et al, 2002]
- Bayesian predictor part as in original

Pr_{basic} (original version)

k	f_1 vi	f_2 ph	f_3 ga	f_4 pr	f_5 mb	f_6 me	f_7 hd	f_8 gc	f_9 od	c
1	no	no	2d	as	a1	1	h2	no	dr	ba
2	no	std	2d	as	a2	1	h5	g2	dw	st
3	sd	std	adv	i4	i2	3	h5	g9	dw	ad
4	hd	adv	adv	i9	i2	4	h9	g9	bw	ad
5	sd	adv	3d	i4	i1	2	h9	g8	dw	st
u	no	no	3d							

"My popularity" (my probabity) $0.4 \times 0.2 \times 0.2 \times 0.4 \times 0.2 \times 0.6 = 0.003072$

"I have popular values in those features that the active user has not selected, so use my feature values!"

$$Pr_{basic}(c, \bar{F_u}) = \prod_{j \in \bar{F}_u} \frac{count(f_j, f_{j,c})}{K}$$

Pr_{basic} (extended version)

k	f_1 **vi**	f_2 **ph**	f_3 **ga**	f_4 **pr**	f_5 **mb**	f_6 **me**	f_7 **hd**	f_8 **gc**	f_9 **od**	c
1	no	no	2d	as	a1	1	h2	no	dr	ba
2	no	std	2d	as	a2	1	h5	g2	dw	st
3	sd	std	adv	i4	i2	3	h5	g9	dw	ad
4	hd	adv	adv	i9	i2	4	h9	g9	bw	ad
5	sd	adv	3d	i4	i1	2	h9	g8	dw	st
u	no	no	3d							

	as	i4	i9
as	0	0.707	1.225
i4	0.707	0	0.707
i9	1.225	0.707	0

A feature value gets support iff neighbor configurations have feature values within maximum distance Δ, here we use Δ=0.8

$(1-(0.707))^2 + (1-(0.707))^2 + (1-0^2) + (1-(0.707))^2 + (1-0^2) = 2.257$

0.0858*3+1*9=9.257

$$s_{f_j}(x,y) = \begin{cases} (1-d_{f_j}(x,y))^2, & \text{if } d_{f_j}(x,y) \leq \Delta \\ 0, & \text{otherwise} \end{cases}$$

The support quickly decreases when the distance increases (square)

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Pr_{basic} of $Conf_5$

$$Pr_{basic}(c, \bar{F}_u) = \prod_{j \in \bar{F}_u} \frac{\sum_{k=1}^{K} s_{f_j}(f_{j,c}, f_{j,k})}{\sum_{v \in dom(f_j)} \sum_{k=1}^{K} s_{f_j}(v, f_{j,k}) * min(1, count(f_j, v))}$$

- For j=pr (processor) and v=i4: 2.257 / 5.601 = 0.4031
- conf5: pr (i4)=0.403, mb (i1)=0.286, me (2)=0.280, hd (h9)=0.444, gc (g8)=0.286, od (dw)=0.600
  → Pr_{basic} = 0.002461

Bayesian predictor

- Bayesian predictor for the user profile u to have the values already selected, given an the existing neighbors (examined by neighbor), $P(f_{j,u}=f_{j,u}|Conf)$
  - Same as in original Cöster formulas
- m-estimate [Bratko et al. 1996] stabilizes probability even in case of (too) few samples
  - Assumes *m* virtual samples with initial probability *p*
  - Future work may improve parameters

$$\prod_{f_j \in F} P(f_{j,u} = f_{j,u}|Conf) = \prod_{f_j \in F} m_{est}(eqcfgs_m(c, F \cup f_j, f_j, f_{j,u}), eqcfgs(c, F), 1/K, K)$$

$$m_{est}(N_c, N, p, m) = \frac{N_c + mp}{N + m}$$

Discussion and Future work (1)

- Evaluation (analytical approach, user studies)
- Implementation with configurator integration
- How to provide recommendations in the user interface
  - As default selections, individualized recommendation indication of alternatives, individualized explanatory texts or help, hide unsuitable values, warn against non-recommended combinations
- Consistency of recommendations vs. (partial) configuration
  - E.g. Should a low-weight incompatible selected value always prevent recommending an otherwise superior alternative of an important feature?

Discussion and Future work (2)

- The algorithms and their parameters (e.g. m-estimate)
  - How to take into account variation of the structure of the product
  - Relatively independent subconfigurations? Or everything affects everything?
  - Varying weights of features with user preferences
- Similarity metrics
  - How to determine applicable classifications for learning similarity?
  - Classifiers based on the whole product, or e.g. by sub-system?
  - Does our approach produce satisfying results? Or is manual determination of similarity needed?
- Reconfiguration with recommendation support
  - Long relationships → changing needs & situations

  → update solution & avoid switching costs or weakening of terms
- Relationship of defaults and recommendations?

Conclusions

- Identified different scenarios for recommendation
- Showed the potential benefits of integrating recommendation with configuration technologies
  - Allows for the derivation of individualized and personalized product and service offerings
  - Potential for reducing the mass confusion phenomenon
  - An important step towards configuration systems which more actively support users in preference construction processes.
- We have developed recommendation approaches
  - To take into account importance weights of features
  - To take into account similarity (substitutes equality)
  - To take consistency into account
- Identified numerous areas of future work

Questions?

Thank you for your attention!