Educating a model student in MOOCs

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AUDIOVISUAL COMMUNICATIONS LCAV

ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Digital Signal Processing (DSP) MOOC at Coursera

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ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

Digital Signal Processing

Paolo Prandoni and Martin Vetterli

Learn the fundamentals of digital signal processing theory and discover the myriad ways DSP makes everyday life more productive and fun.

Digital Signal Processing (DSP) MOOC at Coursera

How to analyze and design the DSP MOOC?

Outline

- The recap scheduling problem in education

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- The Monotonically Decreasing Recap (MDR) schedule

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- Conclusions & future work

MOOCs

Massive Open Online Courses (MOOCs)

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- Players: Coursera, edX, Udacity, ...

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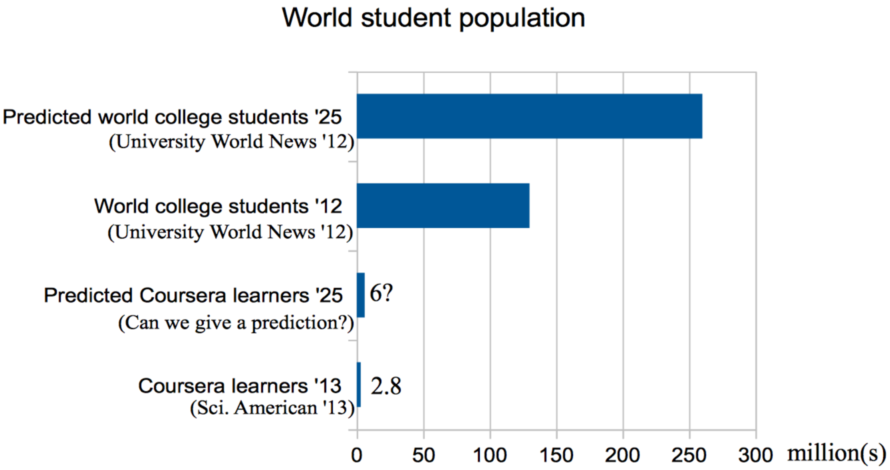
- Players: Coursera, edX, Udacity, ...
- Visibility: $>$ 2.8 million learners on Coursera ('13)

Potential


World student population
Predicted world college students '25
(University World News '12)
World college students '12
(University World News '12)
Predicted Coursera learners '25
(Can we give a prediction?)
6?
Coursera learners '13
(Sci. American '13)
2.8
0
50
100
150
200
250
300
million(s)

Prior work

Research on MOOCs

- Learning sciences community [Blikstein'13] [Ahn'13]

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Prior work

Research on MOOCs

- Learning sciences community [Blikstein'13] [Ahn'13]
- CS community [Novikof'12] [Ghosh'13]
- Others (Science/Nature/NY Times)

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The recap scheduling problem in education

Findings of experimental psychology

- Spacing effect: Better to spread studying over time

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Challenges of MOOCs design

- How to make trade-off between new material and recap?

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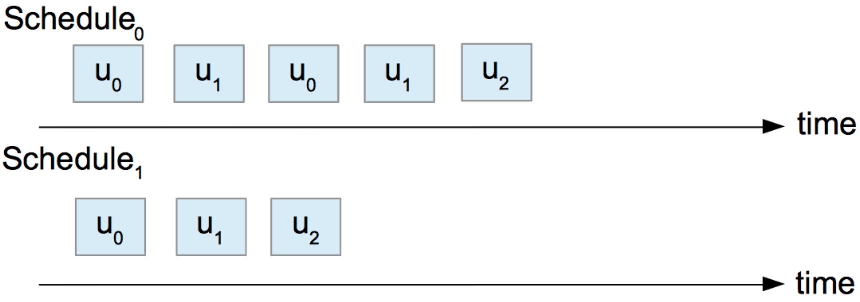
Challenges of MOOCs design

- How to make trade-off between new material and recap?
- How to adapt based on students' feedback?
- Recap schedule needs to satisfy spacing constraints!

Problem illustration



Which schedule gives better studying?

Education of a model student

Novikof, Kleinberg, Strogatz '12, PNAS

- Model the education process as a sequence of abstract units

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Models

- $\{u_i\} = u_1, u_2, u_3, u_1$: u_1 intro at 1^{st} and recap at 4^{th} timesteps

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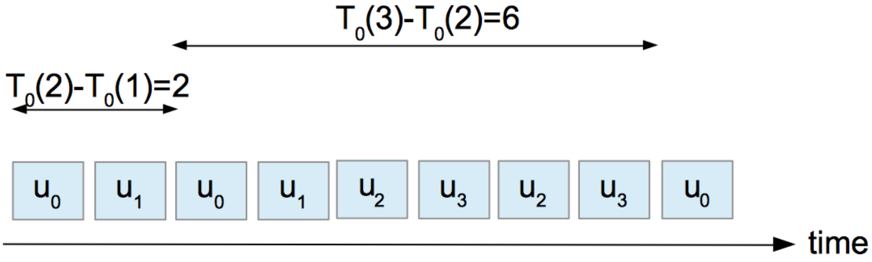
- $a_k \leq |T_n(k+1) - T_n(k)| \leq b_k$
- $a_k \leq a_{k+1}$, $b_k \leq b_{k+1}$ $\forall k$

Model illustration



Models

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Introduction time function $T_n(1)$: the first timestep u_n is introduced

Model	(a_k, b_k)	Asymptotics of $T_n(1)$
Fixed length recap schedule	$(2^k,\ 2^{k-1}(k+1))$	$\Theta(n\ log_2\ n)$
Slow flashcard schedule	$(k,\ k^2)$	$\Theta(n^2)$
Flexible students	$(1,\ k+1)$	$\Theta(n^2)$
Finicky slow students	$(k,\ k)$	None

The Fixed Length Recap (FLR) schedule

$(a_k, b_k) = (2^k, 2^{k-1}(k+1))$, $k = 2$, first 12 units,

$$u_0,\ u_1,\ u_0,\ u_1,\ u_2,\ u_3,\ u_2,\ u_3,\ u_0,\ u_1,\ u_2,\ u_3.$$

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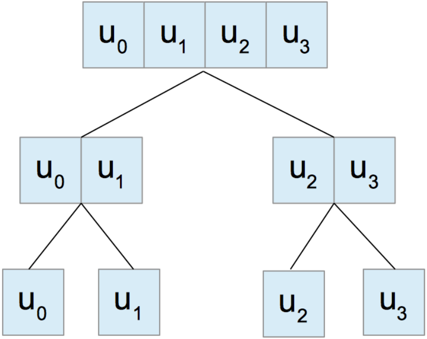
$$u_0, u_1, u_0, u_1, u_2, u_3, u_2, u_3, u_0, u_1, u_2, u_3.$$

DFS traversal



FLR in practice

Problems

- Recap units are usually shorter than new units
- Not all units need recap
- Nonlinear asymptotics: Bad for course planning

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Can we do better?

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The Monotonically Decreasing Recap (MDR) schedule

$(a_k, b_k) = (2^k, 2^{k-1}(k+1))$, $k = 2$, decreasing factor $= 0.5$, first 16 units,

$$u_0,\ u_1,\ u_0,\ u_1,\ u_2,\ u_3,\ u_4,\ u_3,\ u_4,\ u_5,\ u_0,\ u_1,\ u_2,\ u_3,\ u_4,\ u_5,\ u_6,\ u_7.$$

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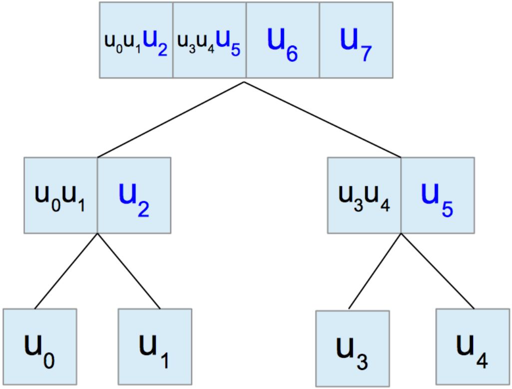
$(a_k, b_k) = (2^k, 2^{k-1}(k+1))$, $k = 2$, decreasing factor $= 0.5$, first 16 units,

$$u_0, u_1, u_0, u_1, u_2, u_3, u_4, u_3, u_4, u_5, u_0, u_1, u_2, u_3, u_4, u_5, u_6, u_7.$$

DFS traversal



Theorem

In the MDR schedule with a decreasing factor $\alpha \leq 0.5$,

$$T_n(1) \text{ grows as } \Theta(n).$$

Proof: Details see report.

$$n \leq T_n(1) \leq 2 \cdot n$$

Asymptotics of $T_n(1)$ for $0.5 < \alpha < 1$ is under investigation ...

Spacing constraints

Theorem

In the MDR schedule with a decreasing factor $\alpha = 0.5$, the units introduced in the leaf nodes adheres to the spacing constraints

$$a_k = 2^k$$
$$b_k = 2^{k-1}(k+1).$$

under the condition that the units introduced in the nonleaf nodes can be arbitrarily distributed in the nodes they are present.

Proof: See report.

MDR in practice

Properties

- Review units are shorter
- Only leaf units satisfy spacing constraints
- Linear schedule

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How to design a MDR for the DSP MOOC?

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MOOC data

Data at hand

- Online forums
- Homework, labs, quizzes, exams
- Survey

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Online forums

- Direct feedback from students
- Collaboration between students and teaching staffs

$$\begin{aligned} \textit{forum data} &= \{\textit{thread}_i\} \\ \textit{thread}_i &= \{\textit{post}_j\} \\ \textit{post}_j &= \textit{post}_j | \{\textit{comment}_k\}. \end{aligned}$$

Concepts of interest in the forum

- Supervised learning approach
- Machine learning software: Kea [Witten'98]
- Human screening of extracted keywords

Concept	Keyphrases
Signal	Gaussian, sinc, ...
Basic math	summation, polynomial, ...
Filter	filter, convolution, FIR, ...
Fourier analysis	Fourier, DFS, DFT, ...
Periodicity	periodic, period
Vector space	Hilbert space, basis, subspace, ...
Sampling	sampling frequency/theorem
Orthogonality	orthonormal, orthogonal
Interpolation	Lagrange/linear interpolation, ...
Wavelet	wavelet, wavelets

Another way to look at forum data

Sequence of posts with tags

$$\begin{gathered} \textit{forum data} = \{p_1, p_2, ..., p_n\}, \\ \text{where } p_k = p_k(\textit{timestamp}, \textit{participant}, \textit{keyphrases}). \end{gathered}$$

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Sequence of posts with tags

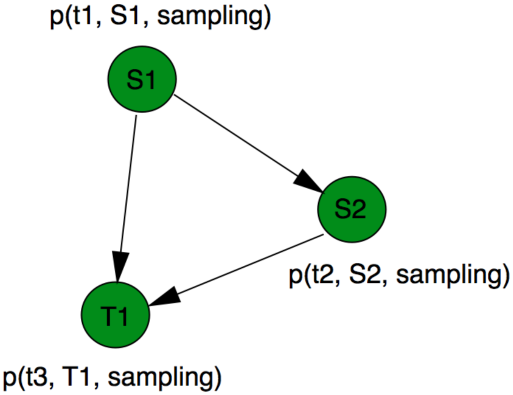
$$\textit{forum data} = \{p_1, p_2, ..., p_n\},$$
$$\text{where } p_k = p_k(\textit{timestamp}, \textit{participant}, \textit{keyphrases}).$$

A forum thread,

$$p_1(t_1, S_1, key), p_2(t_2, S_2, key), p_3(t_3, T_1, key),$$
$$\text{where } t_1 < t_2 < t_3,\ S_1,\ S_2 \text{ are two students}$$
$$T_1 \text{ is a teacher, } key = \text{sampling}$$

Graph of forum data

More visualization (edges follow chronological order) ...



$T1$ is an authoritative source ...

Filtering the seq of forum posts

Raw seq not informative ...

Definition

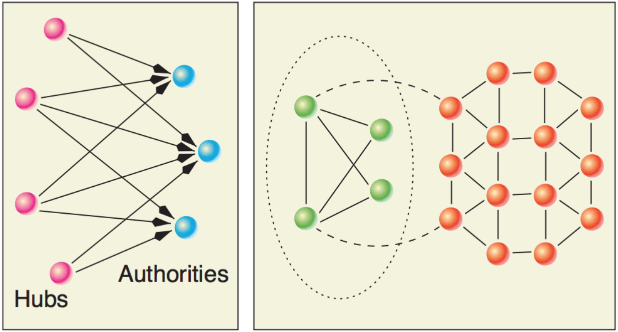
A filtering operation F on the sequence of forum posts $\{p_k\}$, ranks and keeps the n_{top} top-ranked p_k as $\{p'_k\}$

$$F(\{p_k\}, n_{top}) = \{p'_k\}.$$

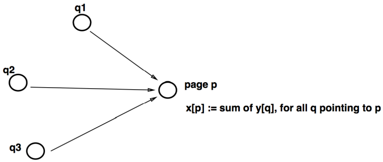
Ex: timestamp, authority, concept filtering ...

HITS algorithm

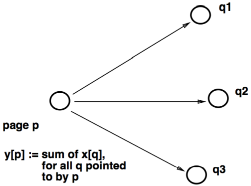
Finding authoritive sources on the web [Kleinberg'01]



HITS algorithm



(c) I Operator



(d) O Operator

HITS algorithm

HITS(G, k)

G: a collection of n linked pages

k: a natural number

Let z denote the vector (1,1,1,...,1) $\in$ Rn. Set $x_0 \leftarrow$ z.

Set $y_0 \leftarrow$ z.

For i = 1, 2, ..., k

Apply the I operation to (x_{i-1}, y_{i-1}), obtaining new x-weights x_i'.

Apply the O operation to (x_i', y_{i-1}), obtaining new y-weights y_i'.

Normalize x_i', obtaining x_i.

Normalize y_i', obtaining y_i.

End

Return (x_k, y_k).

Authority filtering

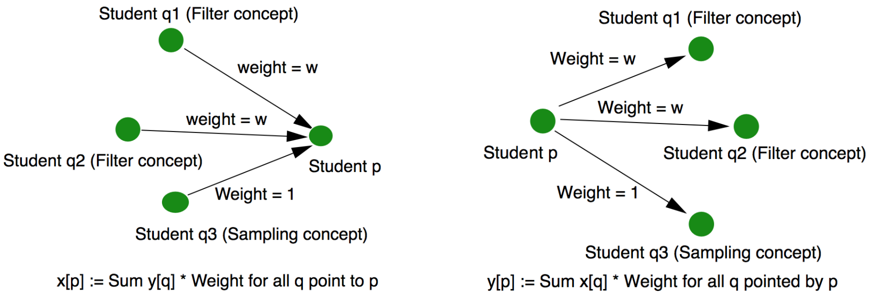
Definition

An authority filtering operation AF on the sequence of forum posts $\{p_k\}$, *ranks and keeps the chronologically ordered posts of the* n_{top} *top-ranked nodes as* $\{p'_k\}$ *by authority weights using HITS Algorithm,*

$$AF(\{p_k\}, n_{top}) = \{p'_k\}.$$

Weighted-HITS algorithm

Emphasize the nodes with posts containing keyphrase K ...



(g) I' Operator

(h) O' Operator

Weighted-HITS algorithm

Given weights $\{x'_p\}$, $\{y'_p\}$, an amplification factor a ($a \geq 1$), the I' operation updates the x-weights as follows.

$$x'_p \leftarrow \sum_{q:(q,p)\in E} \theta(K) \cdot y'_q.$$

The O' operation updates the y-weights as follows.

$$y'_p \leftarrow \sum_{q:(p,q)\in E} \theta(K) \cdot x'_q,$$

where

$$\theta(K) = \begin{cases} a & : p \text{ or } q \text{ has posts containing keyphrase } K \\ 1 & : \text{otherwise} \end{cases}$$

Weighted-HITS algorithm

WeightedHITS (G, k, K)

G: a collection of n linked nodes

k: a natural number

K: a keyphrase

Let z denote the vector $(1, 1, 1, ..., 1) \in R_n$. Set $x_0 \leftarrow z$.

Set $y_0 \leftarrow z$.

For i = 1, 2, ..., k

Apply the I' operation to (x_{i-1}, y_{i-1}), obtaining new x-weights $x'_{i,new}$.

Apply the O' operation to $(x'_{i,new}, y_{i-1})$, obtaining new y-weights $y'_{i,new}$.

Normalize $x'_{i,new}$, obtaining x'_i.

Normalize $y'_{i,new}$, obtaining y'_i.

End

Return (x'_k, y'_k).

Convergence of weighted-HITS

Theorem

The sequences $x'_1, x'_2, x'_3, \ldots$ *and* $y'_1, y'_2, y'_3, \ldots$ *converge (to limits* x'^* *and* y'^* *respectively)*

Proof: See report.

Concept filtering

Definition

A concept filtering operation CF on the sequence of forum posts $\{p_k\}$, *ranks and keeps the chronologically ordered posts of the* n_{top} *top-ranked nodes as* $\{p'_k\}$ *by authority weights using keyphrase* K *and Weighted-HITS algorithm,*

$$CF(\{p_k\}, n_{top}, K) = \{p'_k\}.$$

Nonlinear filtering

Theorem

Authority filtering and concept filtering are nonlinear operations.

Proof: See report.

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Education units of the DSP MOOC (Spr '13)

17 units in 9 weeks ...

Unit	Description
u_0	Introduction to DSP, basic mathematics
u_1	Hilbert space and approximation
u_2	Introduction to DFT
u_3	DFT examples
u_4	DFT, DFS, DTFT
u_5	Relationship between transforms
u_6	Linear filters
u_7	Frequency response
u_8	Realizable filters
u_9	Filter design

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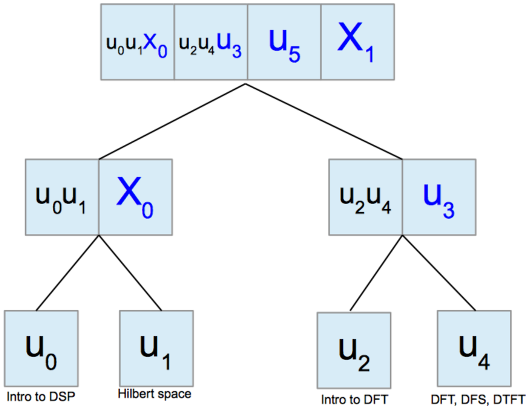
17 units in 9 weeks ...

Unit	Description
u_{10}	Interpolation and bandlimited signals
u_{11}	Sampling and aliasing
u_{12}	Stochastic signal processing
u_{13}	Image processing
u_{14}	Image filtering
u_{15}	Digital communication systems
u_{16}	Modulation and demodulation

Divide and conquer: 3 MDR schedules

MDR schedule for the DSP MOOC (Spr '13)

Recap for $u_0, u_1, u_2, u_3, u_4, u_5$ ...



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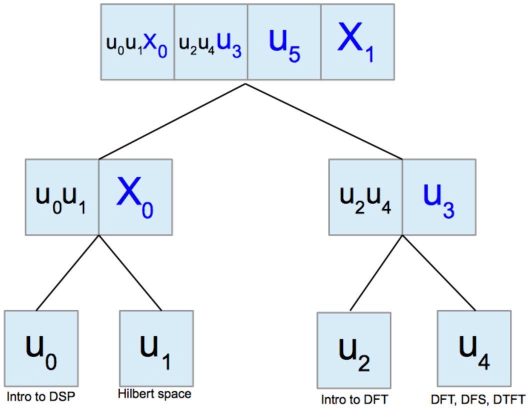
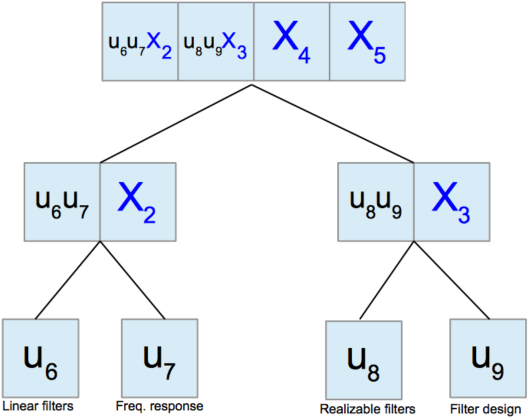


What to recap in X_0, X_1?

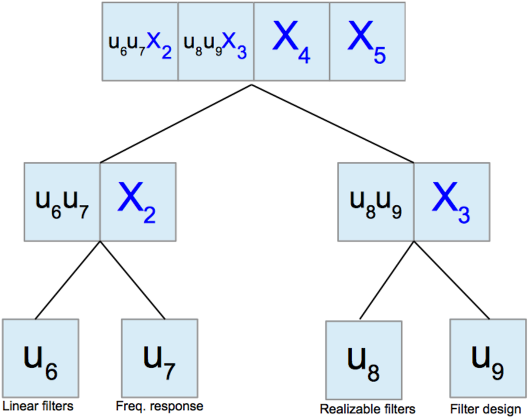
MDR schedule for the DSP MOOC (Spr '13)

Recap for u_6, u_7, u_8, u_9 ...



MDR schedule for the DSP MOOC (Spr '13)

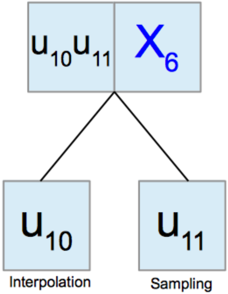
Recap for u_6, u_7, u_8, u_9 ...



What to recap in X_2, X_3, X_4, X_5?

MDR schedule for the DSP MOOC (Spr '13)

Recap for u_{10}, u_{11} ...



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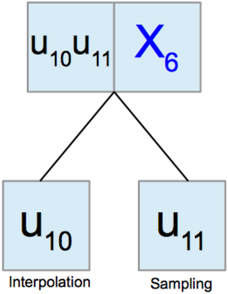
Recap for u_{10}, u_{11} ...



What to recap in X_6?

X_0 recap

X_0 recap

- u_0 (intro to DSP) and u_1 (Hilbert space)

Concept filtering

- Signal, basic math, vector space, orthogonality

X_0 recap

- Q: Floor (w/ discontinuity), constant functions periodic?
- A: Yes ...

- Q: Properties of sinusoids ...
- A: $W_N^{N/2} = \exp(-j2\pi\frac{N}{2N}) = \exp(-j\pi) = -1$ ...

- Q: Properties of the inner product ...
- A: Check the axioms of the inner product ...

X_1 recap

X_1 recap

- u_2 (intro to DFT), u_4 (DFT, DFS, DTFT)

Concept filtering

- Fourier analysis, periodicity

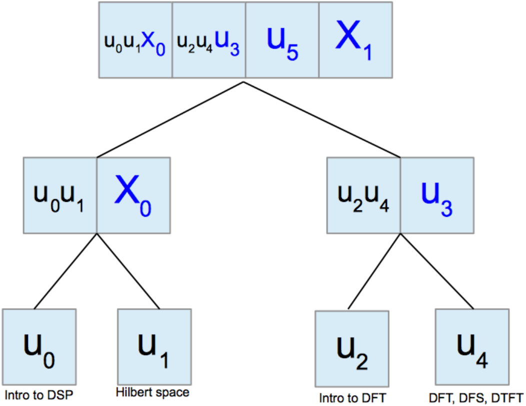
X_1 recap

- Q: Calculation of DTFT ...
- A: The modulation/convolution/linearity properties of DTFT pairs
- A: DTFT pairs of step/sine/sawtooth functions
- A: Properties of a Hermitian operator

- Q: Discrete Fourier Series vs. Discrete Fourier Transform
- A: Fourier analysis for periodic functions and discrete sequences ...

- Q: A factor $\frac{1}{\sqrt{N}}$ in front of both DFT and IDFT?
- A: Factor $\frac{1}{N}$ considered in the IDFT ...

X_1 recap



u0u1X0
u2u4U3
U5
X1
u0u1
X0
u2u4
U3
u0
u1
u2
u4
Intro to DSP
Hilbert space
Intro to DFT
DFT, DFS, DTFT

X_2, X_3, X_4, X_5 recap

X_2, X_3, X_4, X_5 recap

- u_6 (linear filters), u_7 (frequency response)
- u_8 (realizable filters), u_9 (filter design)

Concept filtering

- Filter

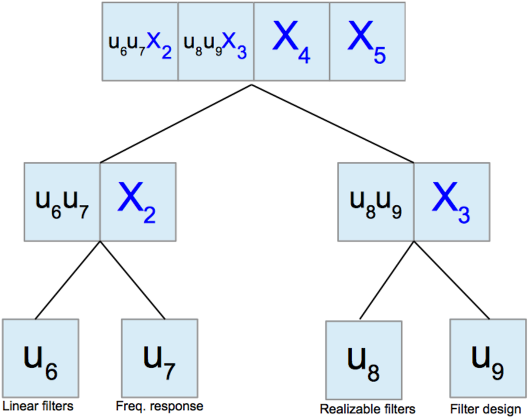
X_2, X_3, X_4, X_5 recap

- Q: Properties of a filter ...
- A: Linearity, stability, causality, linear phase ...

- Q: The transfer function of a filter ...
- A: Analyze the filter regardless of the input ...

- Q: Poles and zeros and filter properties ...
- A: Use ROC inside/outside the unit circle to prove ...
- Q: Moving the poles of a leaky integrator ...
- A: Resulting in a narrow-pass filter ...

X_2, X_3, X_4, X_5 recap



X_6 recap

X_6 recap

- u_{10} (interpolation and bandlimited signals)
- u_{11} (sampling and aliasing)

Concept filtering

- Sampling, interpolation

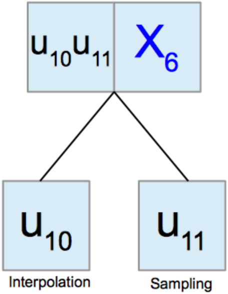
X_6 recap

- Q: Linear and Lagrange interpolation
- A: Use the samples as bases ...

- Q: Sampling at exactly the Nyquist rate ...
- A: Pointwise effect ...
- Q: How to determine the sampling freq?
- A: BW is known at the receiver side ...

- Q: What is the time duration between two samples ...
- A: $\frac{1}{f}$ ...

X_6 recap



Forward projection: DSP MOOC Autumn '13

- $X_0, X_1, X_2, X_3, X_4, X_5, X_6$: Numerical examples

Outline

- The recap scheduling problem in education
- The Monotonically Decreasing Recap (MDR) schedule
- MOOC data processing
- The design of MDR for the DSP MOOC
- Conclusions & future work

Conclusions

The recap scheduling problem in education

- Rich ground for modellization

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- FLR difficult to realize

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Future work

Recap schedule modellization

- Dependency between educational units

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- Dependency between educational units
- Flexible & slow students

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- Flexible & slow students
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Model validation in MOOCs

- Filtering algorithms for MOOC data
- Recap schedule to fit students' needs
- Improve MOOCs

Thank you, questions please.

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