Welcome!

• Please share: Let others know you are here with #HPCCTechTalks

• Ask questions! We will answer as many questions as we can following each speaker.

• Look for polls at the bottom of your screen. Exit full-screen mode or refresh your screen if you don’t see them.

• We welcome your feedback - please rate us before you leave today and visit our blog for information after the event.

• Want to be one of our featured speakers? Let us know! techtalks@hpccsystems.com
Community announcements

Platform updates:

- Latest release now available:
  - 7.2.4 Gold
- More information is available on the improvements and features included the 7.2.x series which include:
  - IDE Improvements
  - Java Embed
  - Alternative ways of embedding C and C++ code
  - Spark Improvements
  - Additions to ECL standard library
  - Thor improvements
  - New geospatial library from Uber.

Read the latest blogs on the community portal

- TextVectors – Machine Learning for Textual Data
- ECL Tips – The Seven Faces (Forms) of LOOP FUNCTION

Catch up on our 5 Questions with a Developer series

- Anupam Sengupta, GuardHat
- Jo Prichard, Data Scientist, LexisNexis Risk Solutions

Information on our annual Community Day event in the Fall coming soon!

- Day 1 includes a hands-on workshop and poster competition
- Day 2 includes both general and breakout sessions
Jeremy Meier
*Undergraduate Student and Research Assistant*
*Clemson University*
jjmeier@g.clemson.edu

Jeremy is a senior undergraduate student, majoring in Computer Science at Clemson University. He is originally from Greenville, South Carolina, and he is conducting research with Dr. Amy Apon's group with a focus on time series analysis. In the past, he has worked with HPCC Systems in the development of text analysis libraries. His other interests include bioengineering and animation.

David Noh
*Undergraduate Student and Research Assistant*
*Clemson University*
dnoh@g.clemson.edu

David is a senior undergraduate student, majoring in Computer Science at Clemson University. He is working on research with a focus on machine learning algorithms and time series analysis. His interests include machine learning algorithms and high performance computing.
Today’s speakers

Roger Dev
Senior Architect
LexisNexis® Risk Solutions
roger.dev@lexisnexisrisk.com

Roger is a Senior Architect working on the Machine Learning Team. Roger has been involved in the implementation and utilization of machine learning and AI techniques for many years, and he has over 20 patents in diverse areas of software technology. Roger has also served as a mentor to a number of HPCC Systems interns and is a strong supporter in our academic community.

Allan Wrobel
Consulting Software Engineer
LexisNexis® Risk Solutions
allan.wrobel@lexisnexis.com

Allan has spent his career working in the technology industry for over 40 years and has been working with databases since the mid-eighties.

Allan has worked with LexisNexis Risk Solutions since 2011 and the inception of LexisNexis Risk Solutions in the UK. Initially working with Data Operations, Allan is now serves as an ECL developer on both Thor and ROXIE. Allan is a passionate ambassador for the HPCC Systems community and has contributed several video tutorials on YouTube for users.
An Investigation into Time Series Analysis

David Noh
Undergraduate Student
and Research Assistant

Jeremy Meier
Undergraduate Student
and Research Assistant
Quick poll:

How large are the time series data sets that you deal with?

See poll on bottom of presentation screen
What is a Time Series?

- A series of data points that are measured at a regular or semi regular interval

Time Series Example

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
</tr>
</thead>
<tbody>
<tr>
<td>date</td>
<td>value</td>
</tr>
<tr>
<td>9/6/2017</td>
<td>531974.19</td>
</tr>
<tr>
<td>9/7/2017</td>
<td>484704.25</td>
</tr>
<tr>
<td>9/8/2017</td>
<td>692655.27</td>
</tr>
<tr>
<td>9/9/2017</td>
<td>420176.85</td>
</tr>
<tr>
<td>9/10/2017</td>
<td>257548.74</td>
</tr>
<tr>
<td>9/11/2017</td>
<td>212416.06</td>
</tr>
<tr>
<td>9/12/2017</td>
<td>410240.57</td>
</tr>
<tr>
<td>9/13/2017</td>
<td>559267.26</td>
</tr>
<tr>
<td>9/14/2017</td>
<td>556496.67</td>
</tr>
<tr>
<td>9/15/2017</td>
<td>813277.37</td>
</tr>
<tr>
<td>9/16/2017</td>
<td>600158.13</td>
</tr>
<tr>
<td>9/17/2017</td>
<td>371246.62</td>
</tr>
<tr>
<td>9/18/2017</td>
<td>319319.61</td>
</tr>
<tr>
<td>9/19/2017</td>
<td>561655.94</td>
</tr>
<tr>
<td>9/20/2017</td>
<td>650556.61</td>
</tr>
<tr>
<td>9/21/2017</td>
<td>599229.85</td>
</tr>
</tbody>
</table>

Regression Data Set

<table>
<thead>
<tr>
<th>Loan ID</th>
<th>Date</th>
<th>Income per month</th>
<th>Loan type</th>
<th>Loan amount</th>
</tr>
</thead>
<tbody>
<tr>
<td>ID207</td>
<td>15/07/18</td>
<td>25000</td>
<td>Car Loan</td>
<td>1000000</td>
</tr>
<tr>
<td>ID190</td>
<td>15/07/18</td>
<td>50000</td>
<td>Home Loan</td>
<td>2500000</td>
</tr>
<tr>
<td>ID007</td>
<td>22/07/18</td>
<td>70000</td>
<td>Personal Loan</td>
<td>1500000</td>
</tr>
<tr>
<td>ID433</td>
<td>29/07/18</td>
<td>45000</td>
<td>Education Loan</td>
<td>4500000</td>
</tr>
<tr>
<td>ID204</td>
<td>29/07/18</td>
<td>20000</td>
<td>Education Loan</td>
<td>5000000</td>
</tr>
<tr>
<td>ID611</td>
<td>08/08/18</td>
<td>80000</td>
<td>Business Loan</td>
<td>9000000</td>
</tr>
<tr>
<td>ID947</td>
<td>17/08/18</td>
<td>60000</td>
<td>Personal Loan</td>
<td>3700000</td>
</tr>
<tr>
<td>ID200</td>
<td>21/08/18</td>
<td>20000</td>
<td>Car Loan</td>
<td>500000</td>
</tr>
<tr>
<td>ID222</td>
<td>29/08/18</td>
<td>30000</td>
<td>Personal Loan</td>
<td>4300000</td>
</tr>
</tbody>
</table>
What is a Time Series?

• Generally, time series have some sort of seasonality or trend.
  • Trend - A component of a time series that shows the overall movement in the series, ignoring the seasonality and any small random fluctuations
  • Seasonality - Presence of variations that occur at specific regular intervals
Why is Stationarity important?

- Stationarity - A *stationary* time series is one whose statistical properties such as mean, variance, autocorrelation are all constant over time.
  - Thus, time series with trends, or with seasonality, are not stationary

- Most Statistical modeling methods assume or require the time series to be stationary to be effective
  - Easier to predict: one simply predicts that statistical properties will be the same in the future just as they have been in the past
How do I know if my series is stationary?

• First, plot the time series and evaluate the variability of the time series
• Review the summary statistics for your data for seasons or random partitions and check for obvious or significant differences.
  • Split your time series into two (or more) partitions and compare the mean and variance of each group
• You can use statistical tests to check if the expectations of stationarity are met or have been violated
  • Augmented Dickey-Fuller test
How do I make my time series stationary?

• Making your data set stationary can usually be accomplished through the use of mathematical transformations
  • Differencing
    • X1, X2, X3,.........Xn
    • Difference of degree 1: (X2 - X1, X3 - X2, X4 - X3,........Xn - X(n-1)
  • Transformation
    • Taking the log, square-root, etc.

• As you might expect, the series can be “untransformed” by reversing the mathematical transformation
What is time series forecasting?

• Involves taking models fit on historical data and using them to predict future observations

• Components, such as trend and seasonality, may also be the most effective way to make predictions about future values, but not always

• The future is completely unavailable and must only be estimated from what has already happened

• Performance is determined by how well a model forecasts the future
The Data Set

- Stored Value Cards
- Around 16,000 total observations
- 115 accounts
- Opening balance values
  - Ranging from 0 – 10,000,000
  - Represent the balance in the account
What is the Simple/Naive Method?

- In this forecasting technique, the value of the new data point is predicted to be equal to the previous data point. The result would be a flat line, since all new values take the previous values.
What is Simple/Moving Averages?

- **Simple Average**
  - The next value is taken as the average of all the previous values.

- **Moving Average**
  - The next value is derived from the averages of successive segments.
Quick poll:

How familiar are you with ARIMA prior to this talk?

See poll on bottom of presentation screen
What is ARIMA?

• **AutoRegressive Integrated Moving Average**
  • A statistical analysis model that uses time series data to either better understand the data set or to predict future trends

• **Autoregression**
  • Model that shows a changing variable that regresses on its own lagged or prior values

• **Integrated**
  • Represents the differencing of raw observations to allow for the time series to become stationary

• **Moving Average**
  • Incorporates the dependency between an observation and a residual error from a moving average model applied to lagged observations.
What is Auto ARIMA?

- Auto ARIMA unlike the ARIMA model chooses the parameters and makes the data stationary.

<table>
<thead>
<tr>
<th>Step</th>
<th>ARIMA</th>
<th>Auto ARIMA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1</td>
<td>Load data</td>
<td>Load data</td>
</tr>
<tr>
<td>Step 2</td>
<td>Pre-process data</td>
<td>Pre-process data</td>
</tr>
<tr>
<td>Step 3</td>
<td>Make data stationary</td>
<td>Fit Auto ARIMA model</td>
</tr>
<tr>
<td>Step 4</td>
<td>Determine D value</td>
<td>Predict/Forecast values</td>
</tr>
<tr>
<td>Step 5</td>
<td>Determine P and Q values</td>
<td>Calculate error</td>
</tr>
<tr>
<td>Step 6</td>
<td>Fit ARIMA model</td>
<td></td>
</tr>
<tr>
<td>Step 7</td>
<td>Predict/Forecast values</td>
<td></td>
</tr>
<tr>
<td>Step 8</td>
<td>Calculate Error</td>
<td></td>
</tr>
</tbody>
</table>
ARIMA vs Auto ARIMA

Results Comparison

- Real Values
- ARIMA 212
- Auto ARIMA

Date:
- 2017-10-01
- 2017-10-08
- 2017-10-15
- 2017-10-22
What are some modern techniques for time series Analysis?

• Facebook Prophet
  • A procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects.
  • It works best with time series that have strong seasonal effects and several seasons of historical data.
  • Prophet is robust to missing data and shifts in the trend, and typically handles outliers well.

• Random Forest
  • A supervised learning algorithm
  • Can be used for both classification and regression problems
Results

Results Comparison

- Real Values
- Auto ARIMA
- Random Forest

Date

2017-10-01
2017-10-08
2017-10-15
2017-10-22
Quick poll:
How likely is it that you will use time series analysis to solve your company’s data problems?

See poll on bottom of presentation screen
Questions?

Jeremy Meier  
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and Research Assistant  
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David Noh  
Undergraduate Student  
and Research Assistant  
dnoh@g.clemson.edu
Quick poll:
Have you encountered situations in which important information was stored as free-form text?

See poll on bottom of presentation screen
TextVectors -- A new HPCC ML bundle

• Turns text into rich numerical data:
  • Words
  • Phrases
  • Sentences

• Completely automatic and unsupervised.

• Encodes the “meaning” of the text.

• Supports direct analysis of the vectors.

• Vectors can be used as features for any ML algorithm.

• Scalable, Parallelized, Enhanced version of the Sent2Vec algorithm.
"You shall know a word by the company it keeps."
- Linguist John Rupert Firth, 1957

Or more rigorously:

"The meaning of a word is closely associated with the distribution of the words that surround it in coherent text."
Understanding Vectorization – A Thought Experiment

- Let’s pick a few words that are fairly closely related:
  - Cat
  - Dog

- Now let’s pick another word that is fairly unrelated:
  - Piston
Thought Experiment -- continued

• There are many sentences in which you could just as likely find dog or cat:
  • A dog / cat is an animal.
  • Dogs / cats can make good pets.
  • I have a companion dog / cat.
  • My son was bitten by a dog / cat.

• Yet there are many sentences about dogs that would not likely be found about cats:
  • My dog weighs 120 pounds.
  • When I throw a ball, my dog brings it back to me.
  • My dog barks whenever the mailman comes.
  • Cocker Spaniels are a medium size dog breed.

• Note that NONE of those sentences are likely to be found about Pistons.
Thought Experiment -- continued

• Now imagine two words for that are interchangeable in any sentence where one is found...

• If we think long enough on this, we have to concede that these two words must have essentially identical meaning – they are perfect synonyms.

• So John Rupert Firth was on to something: “A word is known by the company it keeps”.

• In order to avoid philosophical argument, let’s call this notion of meaning “Contextual Meaning”.

• Contextual Meaning is not absolute. It is a function of the Corpus (i.e. the body of text) upon which it is based.
The contextual hierarchy

Everything that could be said

Everything that has been said

Everything ever written

My Corpus

Another Corpus

Hypothesis:

“Contextual Meaning” approaches “Meaning” as Corpus Size approaches infinity
How do text vectors work?

• Vectors are best thought of as Coordinates in Space
  • A 2D vector [1.5, -3.2] can represent a coordinate in 2D space
  • A 3D vector [-.35, 1.2, 125.4] can represent a coordinate in 3D space
  • An N-Dimensional vector can represent a coordinate in ND space

• Text vectors are typically between 20 and 1000 dimensional.

• To create good text vectors, we only need to find the coordinates for each word so that it is close to all words with similar meaning and distant from all words with dissimilar meaning.

• This is an optimization problem.
Optimizing Text Vectors

- Dog
- Piston
- Cat
Continuous Bag of Words (CBOW) algorithm

Context = [1, 3]

These weights become the word vector for word 1

These weights become the word vector for word N

Target = 2
N-Grams

• N-Grams are combinations of words that imply different meaning than that of the individual words:
  • New York Times
  • High Performance Computing Cluster
  • Traffic Light

• Order of words in N-Grams is significant

• N-Grams may be sequences of any length
  • Unigram – A single word
  • Bigram – Two word sequence
  • Trigram – Three work sequence

• Note: Using e.g., Trigrams usually also includes Bigrams and Unigrams.
Case Study

• Anonymized public records – Violation Descriptions for every legal violation occurring within several US states.

• Violation Descriptions are entered by hand by clerks at 1000s of different courts.
  • Terse
  • Free-form
  • Many non-standardized abbreviations
  • Frequent typos and mis-spellings

• One million different Violation Descriptions.

• In a given year, approximately 300,000 new Violation Descriptions are seen.

• Vocabulary of over 16,000 Unigram words, 100,000 Trigram words.
Case Study Results

- Training took ~40 minutes on a 20 node HPCC Cluster.
- We identified a set of interesting words in the corpus and asked TextVectors for the closest words in meaning:

<table>
<thead>
<tr>
<th>text</th>
<th>closest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Item</td>
<td>Item</td>
</tr>
<tr>
<td>dog</td>
<td>dogs, cat, k9, animal, canine</td>
</tr>
<tr>
<td>boat</td>
<td>motorboat, mb, canoe, aircraft, vessel</td>
</tr>
<tr>
<td>speeding</td>
<td>speeding, speed, spd, speedng, speedig</td>
</tr>
<tr>
<td>light</td>
<td>lgt, ligh, light, lights, lamp</td>
</tr>
<tr>
<td>vehicle</td>
<td>veh, vehiclel, vehic, vehicle, vechile, vechile</td>
</tr>
<tr>
<td>accident</td>
<td>accid, acc, scene, w1, crash</td>
</tr>
<tr>
<td>fish</td>
<td>fishing, trout, clams, creel, stocked</td>
</tr>
</tbody>
</table>
Case Study Results -- continued

- We selected a small set of words and asked TextVectors to rate them by similarity to each word.

<table>
<thead>
<tr>
<th>text</th>
<th>closest Item</th>
</tr>
</thead>
<tbody>
<tr>
<td>dog</td>
<td>k9, animal, canine, fish, trout</td>
</tr>
<tr>
<td>boat</td>
<td>canoe, vessel, vehicle, crash, car</td>
</tr>
<tr>
<td>speeding</td>
<td>speed, sp, speeding, reckless, crash</td>
</tr>
<tr>
<td>light</td>
<td>brake, mirror, vessel, canine, vehicle</td>
</tr>
<tr>
<td>vehicle</td>
<td>car, canoe, vessel, boat, accident</td>
</tr>
<tr>
<td>accident</td>
<td>acc, crash, brake, vehicle, rd</td>
</tr>
<tr>
<td>fish</td>
<td>trout, bass, k9, dog, vessel</td>
</tr>
</tbody>
</table>
Case Study Results -- continued

• We asked TextVectors to identify anomalous words within a set of words. We gave it the set:
  • dog, cat, canine, vehicle, terrier, animal, reckless
  • We asked for the two most anomalous words

<table>
<thead>
<tr>
<th>id</th>
<th>text</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>vehicle</td>
</tr>
<tr>
<td>8</td>
<td>reckless</td>
</tr>
</tbody>
</table>
Case Study Results -- continued

• We provided a set of sentences that were never seen in the training data and asked TextVectors to identify the closest sentences from the training data:

<table>
<thead>
<tr>
<th>text</th>
<th>closest</th>
<th>similarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>bicycles to ride to the right</td>
<td>fail to ride bike to the right,fail to ride to the right side</td>
<td>0.9739537835121155, 0.9556015729904175</td>
</tr>
<tr>
<td>beltvio passenger</td>
<td>safety beltvio passenger,seat belt violation passenger</td>
<td>0.9506689310073853, 0.920316755771637</td>
</tr>
<tr>
<td>burn trash</td>
<td>burn debris waste,burn rubbish waste</td>
<td>0.8604044318199158, 0.8558459877967834</td>
</tr>
<tr>
<td>crash no proof of insurance</td>
<td>no proof of liability insurance,no proof of insurance scene</td>
<td>0.9724310040473938, 0.9707409739494324</td>
</tr>
<tr>
<td>defect tail light pass side</td>
<td>defective pass side tail light,defective tail light pass side</td>
<td>0.987580418586731, 0.987580418586731</td>
</tr>
<tr>
<td>driev w 2 earbuds</td>
<td>dri w 2 earphone,dri w 2 earphones</td>
<td>0.8863240480422974, 0.8565295934677124</td>
</tr>
<tr>
<td>fail to yield fro stat emeg</td>
<td>fail to yield stat emer vhle,fail to yld stat emerg vh1</td>
<td>0.9484548568725586, 0.9448829889297485</td>
</tr>
<tr>
<td>fictitious id to purchase alco</td>
<td>fake id to purchase alcohol,possess fict id to purch alco</td>
<td>0.9547269940376282, 0.9437414407730103</td>
</tr>
<tr>
<td>firearm shoot in veh</td>
<td>discharge firearm in vehicle,disch firearm while in veh</td>
<td>0.9384040236473083, 0.929913528129883</td>
</tr>
<tr>
<td>going wrong way bicycle</td>
<td>ride bicycle wrong way one way,ride bicycle wrong way one way</td>
<td>0.9243994355201721, 0.9243994355201721</td>
</tr>
<tr>
<td>floodway area allow encroachm</td>
<td>allow animal in roadway,rudee rocks unsafe area</td>
<td>0.7987234592437744, 0.7928654551506084</td>
</tr>
</tbody>
</table>
Case Study Results -- continued

• We had a hard time finding a good analogy to solve, but this one seemed reasonable:

<table>
<thead>
<tr>
<th>text</th>
<th>closest item</th>
<th>similarity</th>
</tr>
</thead>
<tbody>
<tr>
<td>fishing is to trout as hunting is to:</td>
<td>hunt, waterfowl, bait, birds, spotlight</td>
<td>0.8278839588165283, 0.716</td>
</tr>
</tbody>
</table>
Paris is to France as London is to ________

\[ \text{vec}(Paris) - \text{vec}(France) + \text{vec}(London) \sim [\text{UK}, \text{England}] \]
New areas for exploration

- I believe we are just scratching the surface with application of this type of technology.
  - Can semantic relationships be discovered as \((\text{word2} - \text{word1})\)?
  - Can we uncover word hierarchies e.g., \text{Animal} \rightarrow \text{Mammal} \rightarrow \text{Carnivore} \rightarrow \text{Canine}?
  - Is there a way to standardize word vectors so that pre-computed vectors can be combined with contextual local meanings
Quick poll:
Do you think Text Vectors might be useful for your projects?

See poll on bottom of presentation screen
Closing

• Thank you for attending.

• Feel free to contact me if you have projects where TextVectors could be helpful.
  • Roger.Dev@LexisNexisRisk.com

• For more information:
  • TextVectors blog article
    • https://hpccsystems.com/blog/TextVectors
  • All my blog articles:
    • https://hpccsystems.com/blogs-rogerdev
Questions?

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ECL Tip Part I: DISTRIBUTE

Bob Foreman
Senior Software Engineer
LexisNexis Risk Solutions
Cluster Skew

100  100  100

+200%, -100%

300  0   0
The **DISTRIBUTE** function distributes records from the *recordset* across the nodes of the target cluster based on the specified *expression*. All records for which the *expression* evaluates the same end up on the same nodes.

Following the distribution process, all subsequent operations should be optimized by using LOCAL operation.

There are four types of DISTRIBUTE methods:
1. Random
2. Expression
3. Index
4. Skew
DISTRIBUTE Methods

1. "Random" DISTRIBUTE

\[ \text{DISTRIBUTE}(\text{recordset}) \]

This form redistributes the \textit{recordset} "randomly" so there is no data skew across nodes, but without the disadvantages the \texttt{RANDOM()} function could introduce. This is functionally equivalent to \textbf{distributing by a hash of the entire record}.

2. Expression DISTRIBUTE

\[ \text{DISTRIBUTE}(\text{recordset}, \text{expression}) \]

This form redistributes the \textit{recordset} based on the specified \textit{expression}, typically one of the HASH functions. Only the bottom 32-bits of the \textit{expression} value are used, so either HASH or HASH32 are the optimal choices. Records for which the \textit{expression} evaluates the same will end up on the same node. DISTRIBUTE implicitly performs a modulus operation if an \textit{expression} value is not in the range of the number of nodes available. If the MERGE option is specified, the \textit{recordset} must have been locally sorted by the \textit{sorts} expressions. This avoids resorting.
HASH Functions

HASH(expressionlist)
HASH32(expressionlist)
HASH64(expressionlist)
HASHCRC(expressionlist)
HASHMD5(expressionlist)

expressionlist – A comma-delimited list of values.

The HASH functions all return a hash value derived from all the values in the expressionlist.

Domains_Dist := DISTRIBUTEDomains_Seq, HASH(zip, TRIM(prim_name), prim_range));
YP_Cont_Dist := DISTRIBUTEDYellowPages_Contacts, HASH32(TRIM(company_name),
TRIM(lname), zip));
DISTRIBUTE Methods

Index-based DISTRIBUTE

DISTRIBUTE(recordset, index [ , joincondition ])

This form redistributes the recordset based on the existing distribution of the specified index, where the linkage between the two is determined by the joincondition. Records for which the joincondition is true will end up on the same node.

Skew-based DISTRIBUTE

DISTRIBUTE(recordset, SKEW( maxskew [, skewlimit ]))

This form redistributes the recordset, but only if necessary. The purpose of this form is to replace the use of DISTRIBUTE(recordset,RANDOM()) to simply obtain a relatively even distribution of data across the nodes. This form will always try to minimize the amount of data redistributed between the nodes.

The skew of a dataset is calculated as:

\[
\text{MAX}(\text{ABS}(\text{AvgPartSize}-\text{PartSize}[\text{node}]) / \text{AvgPartSize})
\]

If the recordset is skewed less than maxskew then the DISTRIBUTE is a no-op. If skewlimit is specified and the skew on any node exceeds this, the job fails with an error message (specifying the first node number exceeding the limit), otherwise the data is redistributed to ensure that the data is distributed with less skew than maxskew.
ECL Tip Part II: Leveraging the Power of HPCC Systems? Use AGGREGATE.

Allan Wrobel
Consulting Software Engineer
LexisNexis Risk Solutions
Quick poll:
Do you already use AGGREGATE?

Do you see AGGREGATE as a ‘complex’ Built-in?

See poll on bottom of presentation screen
AGGREGATE: The 2nd ‘Merge’ TRANSFORM

• 1st Iteration

LEFT
Gender: ‘F’
Calls: “

RIGHT
Gender: ‘F’
Calls: “

RTbl MergePhase(RTbl L,RTbl R) := TRANSFORM
   SELF.Calls := L.Calls + L.Gender + CASE(LENGTH(L.Calls), 0 => '1',2 => '2',4 => '3','4');
   SELF := L;
END;

• Result

SELF
Gender: ‘F’
Calls: ‘F1’
AGGREGATE: The 2\textsuperscript{nd} ‘Merge’ TRANSFORM

- 2\textsuperscript{nd} Iteration

<table>
<thead>
<tr>
<th>LEFT</th>
<th>RIGHT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender: ‘F’</td>
<td>Gender: ‘F’</td>
</tr>
<tr>
<td>Calls: ‘F1’</td>
<td>Calls: ‘F1’</td>
</tr>
</tbody>
</table>

\[
RTbl \text{ MergePhase}(RTbl L, RTbl R) := \text{TRANSFORM} \\
\text{SELF.Calls} := L.Calls + L.Gender + \text{CASE}(\text{LENGTH}(L.Calls), 0 \Rightarrow '1', 2 \Rightarrow '2', 4 \Rightarrow '3', '4')); \\
\text{SELF} := L; \\
\text{END;}
\]

- Result

SELF
Gender: ‘F’
Calls: ‘F1F2’
Quick poll:
Has AGGREGATE been demystified for you?

See poll on bottom of presentation screen
Questions?

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