Reducing readmission rates, a machine learning approach:

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TASA DE REINGRESOS

DEFINICIÓN	Porcentaje de ingresos que se producen en un periodo de tiempo delimitado (periodo ventana) después de un alta previa (episodio índice)
DESCRIPCIÓN	Se considera reingreso a todo ingreso inesperado (ingreso urgente) tras un alta previa en el mismo hospital. Esta definición supera otras vinculadas a limitar el concepto a un reingreso por un diagnóstico principal relacionado con el ingreso previo, ya que se ha comprobado que existen numerosos reingresos claramente relacionados con el ingreso previo pero cuyo diagnóstico principal no esta relacionado con el diagnóstico del primer ingreso. Los reingresos tienen una dependencia con la morbilidad atendida en el hospital y con la comorbilidad de los pacientes. Un parte relevante de los mismos están vinculados a la patología crónica respiratoria y cardiaca que son los grupos de enfermedad que concentran un número importante de los reingresos. Con carácter general, los reingresos pueden ser indicativos de dos situaciones diferenciadas: ·La estabilidad clínica en el curso evolutivo de la patología atendida: En este caso, los reingresos están motivados por complicaciones surgidas después del alta pudiendo, entonces, reflejar un inadecuado seguimiento del paciente tras el alta. ·La estabilidad clínica del paciente en el momento del alta hospitalaria: En este caso, los reingresos pueden indicar un alta de hospitalización prematura. Se utilizan dos periodos de ventana para subclasificar los reingresos: Antes de los 8 días tras el alta previa y desde el 8º al 30º tras el alta previa

FÓRMULA DE CÁLCULO	CONDICIONES DEL CÁLCULO	DATOS QUE INTERVIENEN EN LA CONSTRUCCIÓN DEL INDICADOR	
Numerador: Nº de altas de reingresos. • Reingresos totales: reingresos en un periodo ≤ 30 días desde la fecha del alta previa. • Reingresos < 8 días: reingresos en un periodo < 8 días desde la fecha del alta previa. • Reingresos entre 8 y 30 días: reingresos en un periodo ≥ 8 días y ≤ 30 días desde la fecha del alta previa. Denominador: Número de altas en el periodo de cálculo	**Casos excluidos en el numerador**: Ingresos urgentes de los GRD de la CDM 21 de Lesiones, envenenamientos y efectos tóxicos de fármacos, CDM 22 de Quemaduras, y CDM 25 de Trauma múltiple significativo. **Casos excluidos en el denominador**: Altas por éxitus	Nº de altas con reingresos	Altas de hospitalización
		DEFINICIÓN	**DEFINICIÓN**
		La condición de reingresos en un mismo paciente en un mismo hospital, se hace a partir de la identificación de pacientes para ese mismo hospital y para el mismo año, a partir del número de historia, código de hospital. Para una serie correspondiente a la totalidad de un año se realiza sobre los ingresos índices ocurridos en los primeros 11 meses del año.	Número de casos CMBD hospitalización
		FUENTE	**FUENTE**
		CMBD de hospitalización	CMBD de hospitalización

LACE Score

LACE Score Range	Risk Level	Patient List Color Column in MiChart
13 to 19	Highest	Red
10 to 12	High	Yellow
5 to 9	Moderate	Green
0 to 4	Low	Green

LACE

score

Lace Driven Intervention	Low (1-4)	Moderate (5-9)	High (10-12)	Highest (13-19)	Notes/Details
Standardized Discharge Summary with LACE Score Embedded	X	X	X	X	Some revision of existing MiChart d/c summary template would be required.
Mandatory Inpatient Care Manager Evaluation (Regardless of Trigger Screen)			X	X	
• **Patient/Family Education**: Provide to patient and their family education on the LACE score and what it means in terms of readmission risk				X	Discussion on what can be done to prevent coming back to the hospital (i.e. importance of self-management and keep follow-up appointments.) Review of barriers that may keep the patient from doing what they need to do. Scripted piece.
• **Referrals**: If not enrolled, consider referral to care management program or disease specific management program based on medical and psychosocial needs				X	Ex: GRACE, CCMP, Advanced Heart Failure, etc.
• **Palliative Care and Advance Care planning**: Inpatient palliative care assessment and consult (if appropriate), and advanced care planning discussion				X	➢ Assessment of "Would you be surprised if this patient died in the next 6 months?". ➢ As part of pre-discharge IP/OP transition coordination call, notification to OP would be provided that the consult had occurred. ➢ This could also be an outpatient palliative consult referral. ➢ SW or team discussion with patient/family on advanced care planning and advance directive documents
• **Transition of care**: Pre-discharge inpatient care manager to outpatient care manager/care navigator communication (call/email/MiChart) focused on coordinating the patient's transition of care				X	Requires further definition of protocol if there is no assigned outpatient care manager/care navigator for the patient (for beyond Phase 1).
Pre-Discharge Medication Reconciliation with Pharmacist			X	X	Requires further coordination with inpatient and outpatient pharmacy and dedication of pharmacy resources.
Follow-up Appointment made Pre-Discharge with Appropriate Provider (either primary or specialty care), and Scheduled within "X" days of Discharge	As needed*	As needed*	Within 10 days	Within 7 days	*As needed based on inpatient clinical team judgment
Post Discharge Phone Call within 48 Hours (2 business days)	No mandatory call	Optional**	X	X	** Optional based on clinical judgment.

There are studies that say that Machine Learning can perform better than LACE to predict Readmission*.

So we thought we could try it ourselves!


Predicting all-cause risk of 30-day hospital readmission using artificial neural networks

Mehdi Jamei, Aleksandr Nisnevich, Everett Wetchler, Sylvia Sudat, Eric Liu

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Article | Authors | Metrics | Comments | Media Coverage

Correction
Abstract
Introduction
Methods
Results
Discussion
Conclusions
Software release
Acknowledgments
References

Reader Comments (0)
Media Coverage (0)
Figures

Correction

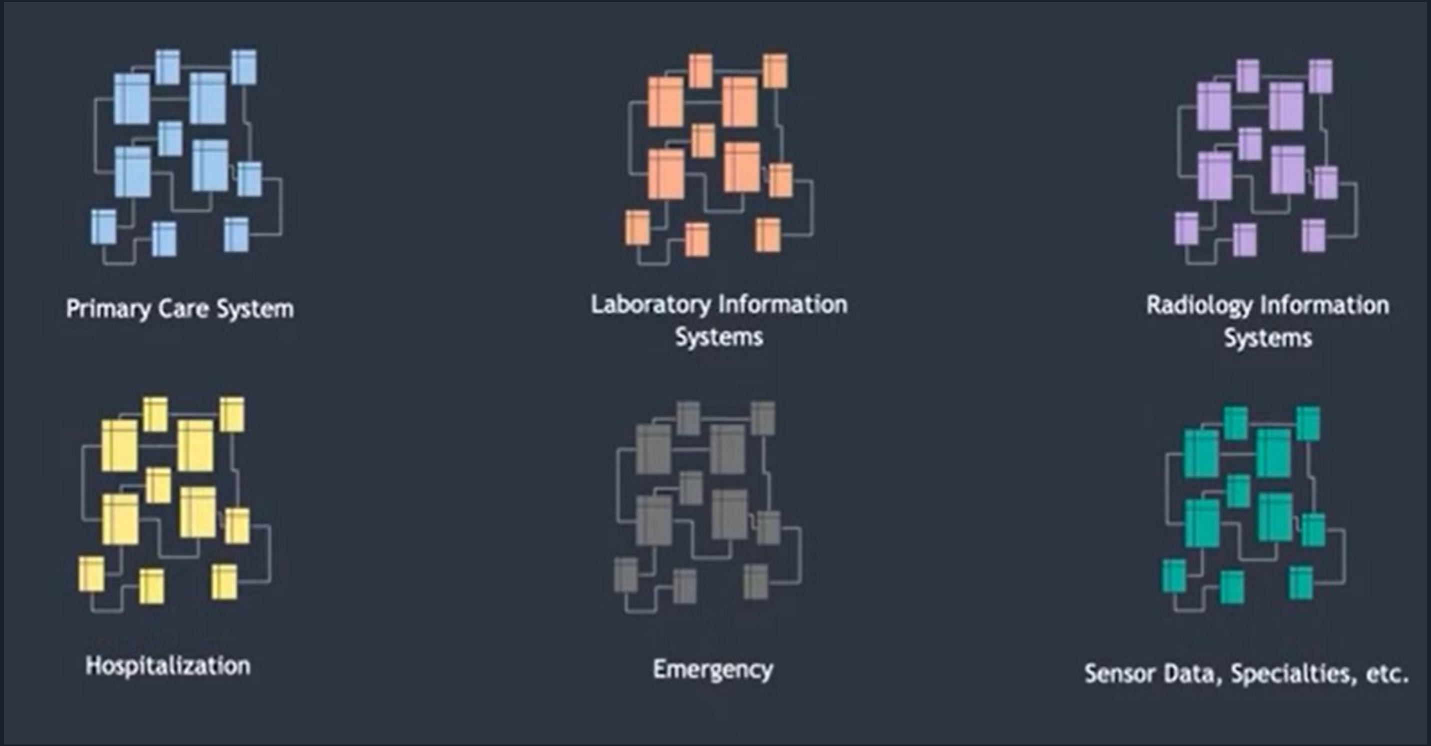
17 May 2018: Jamei M, Nisnevich A, Wetchler E, Sudat S, Liu E, et al. (2018) Correction: Predicting all-cause risk of 30-day hospital readmission using artificial neural networks. PLOS ONE 13(5): e0197793. https://doi.org/10.1371/journal.pone.0197793 | View correction

Abstract

Avoidable hospital readmissions not only contribute to the high costs of healthcare in the US, but also have an impact on the quality of care for patients. Large scale adoption of Electronic Health Records (EHR) has created the opportunity to proactively identify patients with high risk of hospital readmission, and apply effective interventions to mitigate that risk. To that end, in the past, numerous machine-learning models have been employed to predict the risk of 30-day hospital readmission. However, the need for an accurate and real-time predictive model, suitable for hospital setting applications still exists. Here, using data from more than 300,000 hospital stays in California from Sutter Health's EHR system, we built and tested an artificial neural network (NN) model based on Google's TensorFlow library. Through comparison with other traditional and non-traditional models, we demonstrated that neural networks are great candidates to capture the complexity and interdependency of various data fields in EHRs. LACE, the current industry standard, showed a precision (PPV) of 0.20 in identifying high-risk patients in our database. In contrast, our NN model yielded a PPV of 0.24, which is a 20% improvement over LACE. Additionally, we discussed the predictive power of Social Determinants of Health (SDoH) data, and presented a simple cost analysis to assist hospitalists in implementing helpful and cost-effective post-discharge interventions.

* https://doi.org/10.1371/journal.pone.0181173

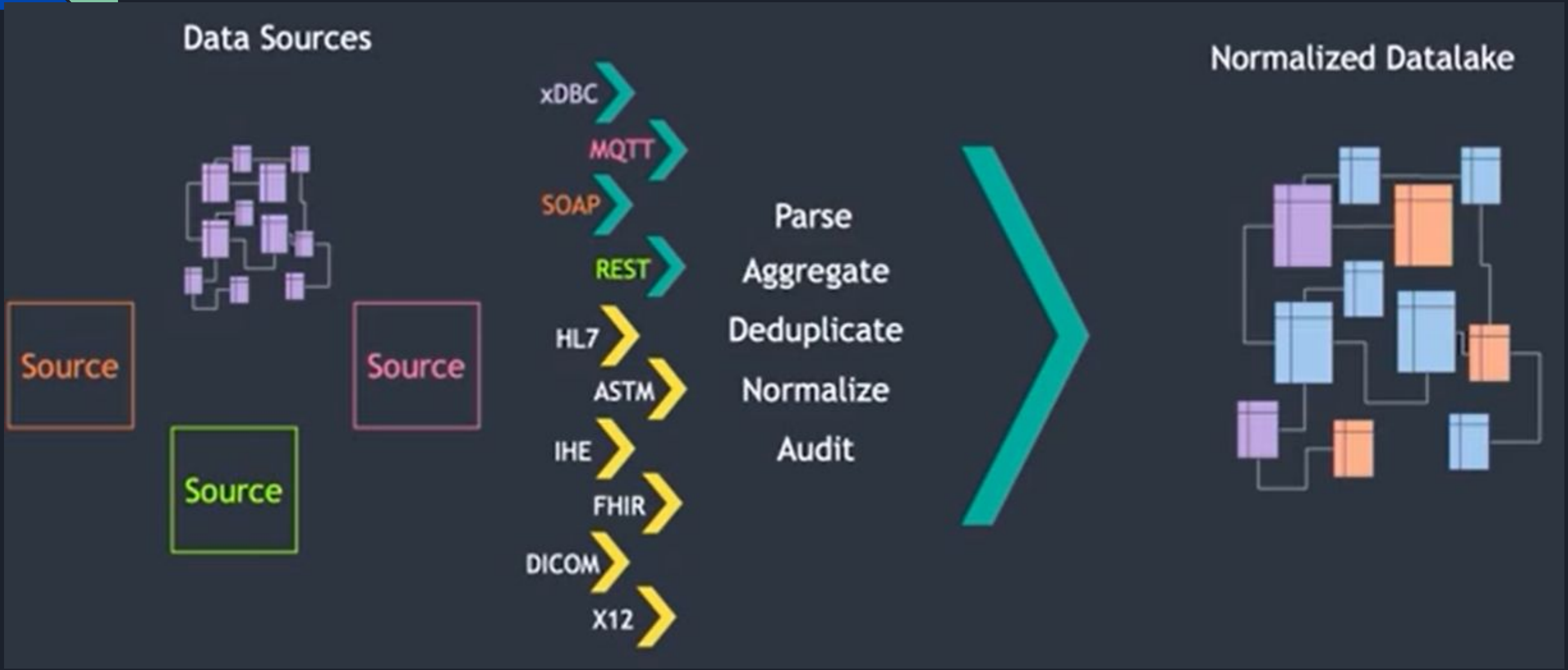
Data Sources



Agregación de datos


Applying LACE now
Risk: 7
2000
Car accident
Smoker
Hypertension
Risk: 9
2011
Bariatric Surgery
Diabetes
Smoker
Hypertension
Risk: 11
2019
Heart Attack
Diabetes
Smoker
Hypertension
Heart Attack
Emergency
At the end, only the hospitalizations must remain. They must aggregate all the data from all past episodes.
Ambulatory
Emergency
Hospitalization

Data normalization




Normalized Datalake
Every problem needs specific data,
aggregated in a specific way
Pipeline
InterSystems IRIS Supporting the Safe Operationalization of Machine Learning
Normalized Datalake
Prepare Data Needed for the Problem
Expose the Data as Needed by the Algorithms
TensorFlow
Spark

Preparación de datos para nuestro problema

Incomplete, just a sample of the full star schema...

ID	Com
1	Asthma
2	Diabetes
3	...
...	...

Com	LOS	Smoker	Discharge Dest	Will Readmit?
	5	0	1	0
2	3	1	1	0
1	5	0	2	1
1,2	4	1	2	1
3	8	1	1	0

ID	Discharge Dest
1	Home
2	Nursing Home
3	Deceased
...	...

One Hot Encoding

ID	Com
1	Asthma
2	Diabetes
3	...
...	...

Com	LOS	Smoker	Discharge Dest
	5	0	1
2	3	1	1
1	5	0	2
1,2	4	1	2
3	8	1	1

ID	Discharge Dest
1	Home
2	Nursing Home
3	Deceased
...	...

One Hot Encoding

Com	LOS	Smoker	Discharge Dest
	5	0	1
2	3	1	1
1	5	0	2
1,2	4	1	2
3	8	1	1

Decision Tree-based algorithms

C_Asthma	C_Diabetes	?	LOS	Discharge Dest
0	0	0	5	1
0	1	0	3	1
1	0	0	5	2
1	1	0	4	2
1	1	1	8	1

One Hot Encoding

Deep Learning likes Full One-Hot Encoding...

Com	LOS	Smoker	Discharge Dest
	5	0	1
2	3	1	1
1	5	0	2
1,2	4	1	2
3	8	1	1

Decision Tree-based algorithms

C_Asthma	C_Diabetes	?	LOS	Discharge Dest
0	0	0	0.4	1
0	1	0	0.0	1
1	0	0	0.4	2
1	1	0	0.2	2
1	1	1	1.0	1

Deep Learning

C_Asthma	C_Diabetes	?	LOS	DD_Home	DD_NHome
0	0	0	0.4	1	0
0	1	0	0.0	1	0
1	0	0	0.4	0	1
1	1	0	0.2	0	1
1	1	1	1.0	1	0

Normalization

Deep Learning also likes normalization. There are several ways of doing it.

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Rescaling (Min-Max Normalization)

$$x' = \frac{x - \text{average}(x)}{\max(x) - \min(x)}$$

Mean Normalization

$$x' = \frac{x - \bar{x}}{\sigma}$$

Standardization

$$x' = \frac{x}{\|x\|}$$

Scaling to Unit Length

Which Normalization is best for my problem?

Com	LOS	Smoker	Discharge Dest
	5	0	1
2	3	1	1
1	5	0	2
1,2	4	1	2
3	8	1	1

Min-Max Normalization?

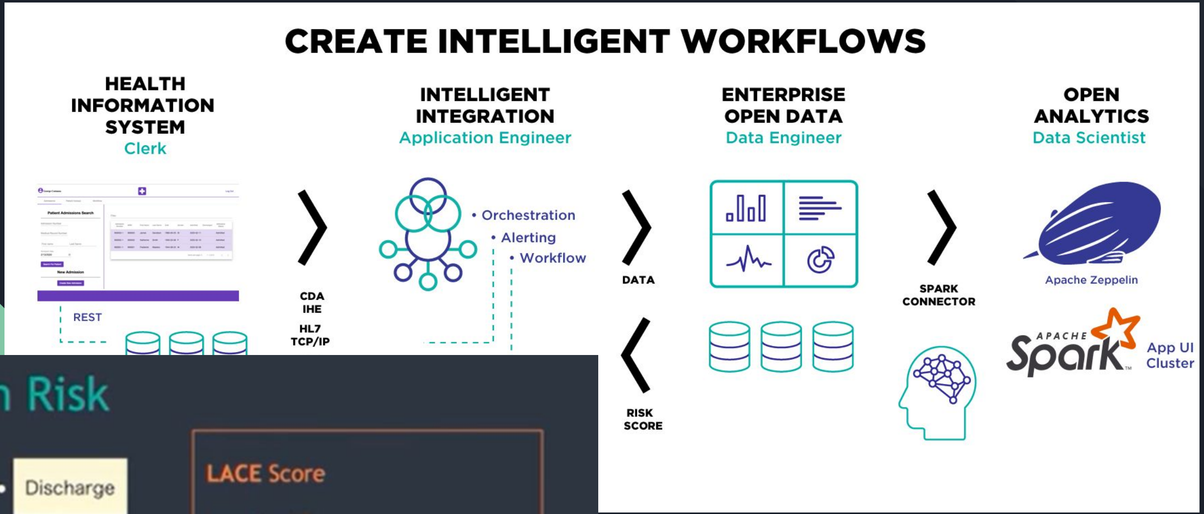
C_Asthma	C_Diabetes	?	LOS	DD_Home	DD_NHome
0	0	0	0.4	1	0
0	1	0	0.0	1	0
1	0	0	0.4	0	1
1	1	0	0.2	0	1
1	1	1	1.0	1	0

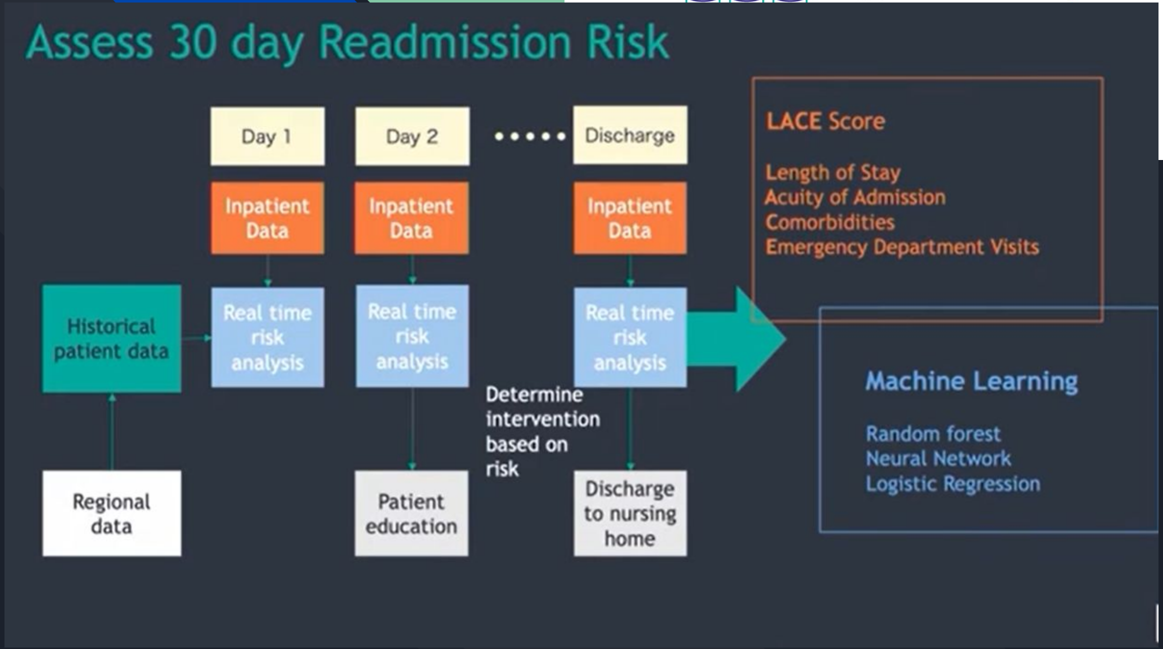
Mean Normalization?

C_Asthma	C_Diabetes	?	LOS	DD_Home	DD_NHome
0	0	0	0.0	1	0
0	1	0	-0.4	1	0
1	0	0	0.0	0	1
1	1	0	-0.2	0	1
1	1	1	0.6	1	0

Standardization?

C_Asthma	C_Diabetes	?	LOS	DD_Home	DD_NHome
0	0	0	0.0	1	0
0	1	0	-1.069	1	0
1	0	0	0.0	0	1
1	1	0	-0.534	0	1
1	1	1	1.6035	1	0


CREATE INTELLIGENT WORKFLOWS
HEALTH INFORMATION SYSTEM
Clerk
INTELLIGENT INTEGRATION
Application Engineer
ENTERPRISE OPEN DATA
Data Engineer
OPEN ANALYTICS
Data Scientist
REST
CDA
IHE
HL7
TCP/IP
• Orchestration
• Alerting
• Workflow
DATA
RISK SCORE
SPARK CONNECTOR
Apache Zeppelin
APACHE Spark
App UI
Cluster


Assess 30 day Readmission Risk
Day 1
Day 2
Discharge
Inpatient Data
Inpatient Data
Inpatient Data
Historical patient data
Real time risk analysis
Real time risk analysis
Real time risk analysis
Regional data
Patient education
Determine intervention based on risk
Discharge to nursing home
LACE Score
Length of Stay
Acuity of Admission
Comorbidities
Emergency Department Visits
Machine Learning
Random forest
Neural Network
Logistic Regression

UniVerse

a text file containing comments that describe how to add additional entries. The default *uvodbc.config* file looks like this:

```
*** To get to any ODBC source other than UniVerse, you need entries
*** that look as follows (the data source must also be configured
*** via the operating system's own mechanisms):
***
*** <data source name>
*** DBMSTYPE = ODBC
***
*** The local DataStage Server Engine is available via the data
*** source name "localuv" as defined below - please do not alter
*** this entry!
***
*** To access a remote UniVerse database, you need another entry
*** similar to that for localuv but with a remote host name in
*** place of "localhost".
***
*** To access a (coresident) UniVerse on the local machine, you
*** need to specify your local machine name or IP address in place
*** of "localhost".
***
*** Note that the spaces around the " = " signs are required, and
*** the data source name must be enclosed in angle brackets "<>".
***
[ODBC DATA SOURCES]
<localuv>
DBMSTYPE = UNIVERSE
network = TCP/IP
service = uvserver
host = localhost
```