Mi Dai

Rutgers University

on behalf of the PLAsTiCC Team:

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The Large Synoptic Telescope (LSST)



Credit: LSST Project/NSF/AURA

This telescope will produce the deepest, widest, image of the Universe:

- 27-ft (8.4-m) mirror, the width of a singles tennis court
- 3200 megapixel camera
- Each image the size of 40 full

moons

- 37 billion stars and galaxies
- 10 year survey of the sky
- 10 million alerts, 1000 pairs of exposures, 15 Terabytes of data .. every night!









2

Plotted using the Open Supernova Catalog

Pre-PLAsTiCC: SNPhotCC

SUPERNOVA PHOTOMETRIC CLASSIFICATION CHALLENGE Richard Kessler,^{1,2} Alex Conley,³ Saurabh Jha,⁴ Stephen Kuhlmann⁵

Results from the Supernova Photometric Classification Challenge

RICHARD KESSLER,^{1,2} BRUCE BASSETT,^{3,4,5} PAVEL BELOV,⁶ VASUDHA BHATNAGAR,⁷ HEATHER CAMPBELL,⁸ ALEX CONLEY,⁹ JOSHUA A. FRIEMAN,^{1,2,10} ALEXANDRE GLAZOV,⁶ SANTIAGO GONZÁLEZ-GAITÁN,¹¹ RENÉE HLOZEK,¹² SAURABH JHA,¹³ STEPHEN KUHLMANN,¹⁴ MARTIN KUNZ,¹⁵ HUBERT LAMPEITL,⁸ ASHISH MAHABAL,¹⁶ JAMES NEWLING,³ ROBERT C. NICHOL,⁸ DAVID PARKINSON,¹⁷ NINAN SAJEETH PHILIP,¹⁸ DOVI POZNANSKI,^{19,20} JOSEPH W. RICHARDS,^{20,21} STEVEN A. RODNEY,²² MASAO SAKO,²³ DONALD P. SCHNEIDER,²⁴ MATHEW SMITH,²⁵ MAXIMILIAN STRITZINGER,^{26,27,28} AND MELVIN VARUGHESE²⁹

- Held in 2010
- Classification on SN Ia and Core-collapse
- Within the astronomy community
- Sample size ~ several thousands
- The post-challenge data has been used for developing methods for photometric classification of supernovae

Why citizen science?

- · Citizen science is vital for astronomy
- Industry drives rapid advances in machine learning (ML)
- LSST data rate demands ML for identifying time-domain events
- Citizen scientists now include thousands of ML experts
- Kaggle provides a platform for ML experts to tackle interesting supervised-learning questions



The "Challenge"

- Types are unbalanced
- Small number in the training set
- The training set is not representative of the test data
- Season gaps
- Non-uniform cadence
- Unknown Class 99

Simulation



Kessler et al. 2019

Summary of Models used in PLAsTiCC

model class	model		Nevent	Nevent	Nevent	redshift
num ^a : name	description	contributor(s) ^b	Gen ^c	train ^d	$test^e$	range ^f
90: SNIa	WD detonation, Type Ia SN	RK	$16,\!353,\!270$	2,313	1,659,831	< 1.6
67: SNIa-91bg	Peculiar type Ia: 91bg	SG,LG	1,329,510	208	40,193	< 0.9
52: SNIax	Peculiar SNIax	SJ,MD	8,660,920	183	63,664	< 1.3
42: SNII	Core Collapse, Type II SN	SG,LG:RK,JRP:VAV	59,198,660	1,193	1,000,150	< 2.0
62: SNIbc	Core Collapse, Type Ibc SN	VAV:RK,JRP	22,599,840	484	175,094	< 1.3
95: SLSN-I	Super-Lum. SN (magnetar)	VAV	90,640	175	35,782	< 3.4
15: TDE	Tidal Disruption Event	VAV	58,550	495	13,555	< 2.6
64: KN	Kilonova (NS-NS merger)	DK,GN	43,150	100	131	< 0.3
88: AGN	Active Galactic Nuclei	SD	175,500	370	101,424	< 3.4
92: RRL	RR lyrae	SD	200,200	239	197,155	0
65: M-dwarf	M-dwarf stellar flare	SD	800,800	981	93,494	0
16: EB	Eclipsing Binary stars	AP	220,200	924	96,572	0
53: Mira	Pulsating variable stars	RH	1,490	30	1,453	0
6: μ Lens-Single	μ -lens from single lens	RD,AA:EB,GN	2,820	151	1,303	0
991: μ Lens-Binary	μ -lens from binary lens	RD,AA	1,010	0	533	0
992: ILOT	Intermed. Lum. Optical Trans.	VAV	4,521,970	0	1,702	< 0.4
993: CaRT	Calcium Rich Transient	VAV	2,834,500	0	9,680	< 0.9
994: PISN	Pair Instability SN	VAV	$5,\!650$	0	1,172	< 1.9
995: μ Lens-String	μ -lens from cosmic strings	DC	30,020	0	0	0
TOTAL	Sum of all models		117, 128, 700	7,846	3,492,888	-

Model Contributors: AA: Arturo Avelino (Harvard U.) EB: Etienne Bachelet (LCO) DC: David Chernoff (Cornell U.) MD: Mi Dai (Rutgers U.) SD: Scott Daniel (U.Washington) RD: Rosanne Di Stefano (Harvard U.) LG: Lluís Galbany (U.Pitt) SG: Santiago González-Gaitán (U.Lisbon) RH: Renée Hlozek (U.Toronto) SJ: Saurabh Jha (Rutgers U.) DK: Dan Kasen (U.C. Berkeley) RK: Rick Kessler (U.Chicago) GN: Gautham Narayan (STScl) JRP: Justin Pierel (U. South Carolina) AP: Andrej Prsa (Villanova U.) VAV: Ashley Villar (Harvard U.)

^anum>990 were all in unknown class 99 during the competition. An extra digit is added here to distinguish each model.

^bCo-author initials. Colon separates independent methods.

 $^{\rm c}$ Number of generated events, corresponding to the true population without observational selection bias.

^dLabeled subset from spectroscopic classification. $0 \rightarrow$ predicted from theory, not convincingly observed, or very few observations.

^eUnlabeled sample. PLAsTiCC goal is to label this sample.

 $^{\rm f}{\rm Redshift} > 0$ for extragalactic models; Redshift= 0 for Galactic models.

Unblinded Data Files: http://doi.org/10.5281/zenodo.2539456

Simulation Source code: <u>http://snana.uchicago.edu</u>

Kessler et al. 2019 Slide credit: Rick Kessler



Kessler et al. 2019





Validation Efforts

Because we have SIMULATED data, there are several areas where we may introduce biases or non-physical correlations:

- •Every box is a potential source for errors
- •The source code was used to generate this data set, but it has never been used for galactic transients
- •3 million new SEDs added as inputs to the simulations!
- •New codes and SEDs are an excellent source of bugs !



Kessler et al. 2019

Slide credit: Kara Ponder

Validation Efforts

Method to the Madness: How to validate PLAsTiCC



- We created a private GitHub repository with a skeleton jupyter notebook and python3 environment.
- Each model had at least two validators each time the full set of simulations were regenerated
- A data scientist from Kaggle also reviewed our data

Slide credit: Kara Ponder

distance

modulus

The Metric

- The metric needs to be probabilistic
- The metric depends on the science goal
- We need to select a metric that balances a variety of goals

The Metric

- The metric needs to be probabilistic
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The Metric

$$\text{Log Loss} = -\left(\frac{\sum_{i=1}^{M} w_i \cdot \sum_{j=1}^{N_i} \frac{y_{ij}}{N_i} \cdot \ln p_{ij}}{\sum_{i=1}^{M} w_i}\right)$$

- The metric needs to be probabilistic
- The metric depends on the science goal
- We need to select a metric that balances a variety of goals



Kaggle Competition

Featured Prediction Competition

PLAsTiCC Astronomical Classification

Can you help make sense of the Universe?

LSST Project · 1,094 teams · 7 months ago

Overview	Data	Kernels	Discussion	Leaderboard	Rules	Team	My Submissions	Late Submission

Overview

Description

Evaluation

Prizes

Timeline

PLAsTiCC's Team

Help some of the world's leading astronomers grasp the deepest properties of the universe.

The human eye has been the arbiter for the classification of astronomical sources in the night sky for hundreds of years. But a new facility -- the Large Synoptic Survey Telescope (LSST) -- is about to revolutionize the field, discovering 10 to 100 times more astronomical sources that vary in the night sky than we've ever known. Some of these sources will be completely unprecedented!



The Photometric LSST Astronomical Time-Series Classification Challenge (PLAsTiCC) asks Kagglers to help prepare to classify the data from this new survey. Competitors will classify astronomical sources that vary with time into different classes, scaling from a small training set to a very large test set of the type the LSST will discover.

More background information is available here.

\$25,000 Prize Money

A Kaggler's journey to PLAsTiCC solutions



Leaderboard

PLAs Can yo	TiCC . ou help ST Projec	Astronomical (make sense of the ct + 1,094 teams + 7 mo	Classification Universe?			\$25, Prize N	Money	
Overviev	v Data	Kernels Discussion	n Leaderboard Rules Team	My Subr	nissions	Late Subm	ission	
Public Lo	eaderboa	rd Private Leaderb	oard					
The priva This com	ate leader apetition l	board is calculated with has completed. This lea	n approximately 67% of the test data. derboard reflects the final standings.			C R	efresh	
📕 In the r	noney	Gold Silver	Bronze					
#	∆pub	Team Name	Kernel	Team Members	Score 🛛	Entries	Last	
1	-	Kyle Boone		94	0.68503	104	7mo	
2	^ 2	Mike & Silogram		<u>R</u> 🙇	0.69933	176	7mo	
3	• 1	Major Tom		10 kg 💽	0.70016	366	7mo	
4	• 1	AhmetErdem			0.70423	233	7mo	
5		SKZ Lost in Translat	ion	💽 🐴 🔝 些	0.75229	337	7mo	
6	^ 2	Stefan Stefanov		9	0.80173	28	7mo	
7	• 3	hklee			0.80836	63	7mo	
8	• 1	rapids.ai		NAR55	0.80905	133	7mo	
9	• 3	Three Musketeers		<u>a</u>	0.81312	313	7mo	
10		10.1		M	0.01001	0.40	-	

Team scores over time





Solutions posted on Kaggle

55		٢	#13 Solution, true story: tries and fails Blonde 16 days ago	last comment by SooperDoop 8d ago	9 19
15		٢	PostProcess Trick - 21st place Partial Solution fatihöztürk 16 days ago	last comment by Murat KORKMAZ 16d ago	9 3
22	¥.	٢	21st Solution -super tough road- takuoko 16 days ago	last comment by takuoko 16d ago	9 11
24		٢	19th Place Solution ONODERA 16 days ago	last comment by Vig Nam 15d ago	9 4
28		٢	11th solution - very basic but may different methods SimonChen 16 days ago	last comment by SimonChen 13d ago	9 15
11	-	٢	A solution and some learnings Helgi 15 days ago	last comment by Avinash Tayade 14d ago	9 4
17	TOUTH WALK WALK ALONE	٢	12th Place Solution Daniel Bi 15 days ago	last comment by go5paopao 7d ago	9 4
32		٢	20th Place Solution Giba 15 days ago	last comment by Giba 14d ago	9 7
20		٢	9th place solution Albert Garreta 14 days ago	last comment by Albert Garreta 11d ago	9 4





Useful Features

- Light curve fitting -- Bazin, GP, template fitting (SALT2, SN templates)
- Flux ratio (color)
- Flux difference
- Host galaxy photo-z
- flux * distance ** 2



Figure credit: Kyle Boone

Popular Models among Kagglers



Binary Classification

	Confusion Matrix : Kyle Boone															
SNIa -	0.82	0.04	0.02	0.00	0.02	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	
SNIa-91bg -	0.05	0.72	0.02	0.00	0.11	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.09	
SNIax -	0.27	0.10	0.25	0.00	0.11	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.23	- 0.8
SN-II -	0.14	0.02	0.06	0.00	0.03	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.69	0.0
SN-lbc -	0.07	0.14	0.05	0.00	0.44	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.26	
TDE -	0.03	0.00	0.00	0.00	0.00	0.87	0.01	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.03	-0.6
SLSN-I -	0.02	0.00	0.00	0.00	0.01	0.01	0.89	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.07	0.0
KN -	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.94	0.00	0.00	0.00	0.00	0.00	0.00	0.04	
AGN -	0.01	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.92	0.00	0.00	0.00	0.00	0.00	0.03	
RRlyrae -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.97	0.00	0.03	0.00	0.00	0.00	0.4
Mdwarf -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.00	0.00	0.00	
EBE -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.98	0.00	0.00	0.00	
MIRA -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.98	0.01	0.00	0.2
uLens-Single -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.93	0.00	
Other -	0.02	0.04	0.07	0.00	0.17	0.02	0.09	0.01	0.01	0.00	0.01	0.00	0.00	0.03	0.53	
	SMID	916	Shiat	SNII	SN-1DC	TOF	GLSN'	42	ACH	allyrae	ndwart	EBE	MIRA	Sinc	other other	0.0
	Ċ	MIS			,					¢.	4.		l.	ensi		
							Predi	cted	labe				v			

Confusion Matrices

True label

					Co	nfusio	n Mat	rix : M	ike & 🗄	Silogra	am					
SNIa -	0.72	0.03	0.06	0.02	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14	
SNIa-91bg -	0.02	0.78	0.03	0.01	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	
SNIax -	0.20	0.06	0.41	0.02	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.27	. ^ 0
SN-II -	0.10	0.01	0.11	0.36	0.02	0.14	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.25	0.0
SN-lbc -	0.04	0.15	0.13	0.08	0.30	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.25	
TDE -	0.01	0.00	0.00	0.00	0.00	0.91	0.01	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.03	0.6
SLSN-I -	0.00	0.00	0.00	0.07	0.00	0.01	0.88	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.0
KN -	0.00	0.02	0.00	0.01	0.01	0.00	0.00	0.95	0.00	0.00	0.00	0.00	0.00	0.00	0.02	
AGN -	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.97	0.00	0.00	0.00	0.00	0.00	0.01	0.4
RRlyrae -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.98	0.00	0.01	0.00	0.01	0.00	- 0.4
Mdwarf -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.00	0.01	0.00	
EBE -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.00	0.00	
MIRA -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.96	0.03	0.00	- 0.2
uLens-Single -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	
Other -	0.02	0.04	0.17	0.28	0.11	0.02	0.09	0.01	0.01	0.00	0.00	0.00	0.00	0.04	0.20	
	SMID	alp	SMIAT	SNII	CN-1DC	TOF	(15M)	4	ACH	alyrae	. dwart	EBE	MIRA	Sint	le ther	 - 0.0
	Ċ	M ³			-)		-)		•	62.	412		5	ensi	-	
							Predi	cted	labe	I						

Confusion Matrices

True label

Class 99

- Designed to encourage anomaly detection methods
- Kagglers ended up probing the Leaderboard

					(Confus	sion M	atrix -	No Cla	ass 99	: Kyle	Boone	9						
	SNIa -	0.83	0.05	0.03	0.02	0.04	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00			
	SNIa-91bg -	0.05	0.73	0.03	0.03	0.14	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00			
	SNIax -	0.29	0.12	0.30	0.07	0.19	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	- 0 8		
	SN-II -	0.17	0.03	0.10	0.55	0.09	0.05	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.0		
	SN-lbc -	0.09	0.15	0.07	0.07	0.57	0.02	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00			
	TDE -	0.04	0.00	0.01	0.02	0.01	0.88	0.01	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.00			
ē	SLSN-I -	0.02	0.00	0.00	0.03	0.02	0.01	0.90	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	- 0.6		
e lab	KN -	0.01	0.02	0.00	0.00	0.03	0.00	0.00	0.94	0.00	0.00	0.00	0.00	0.00	0.00	0.00			
Tru	AGN -	0.01	0.01	0.00	0.01	0.01	0.03	0.00	0.00	0.92	0.00	0.00	0.00	0.00	0.00	0.00			
	RRlyrae -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.97	0.00	0.03	0.00	0.00	0.00	- 0.4		
	Mdwarf -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.00	0.00	0.00			
	EBE -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.98	0.00	0.00	0.00			
	MIRA -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.98	0.01	0.00	- 0.2		
	uLens-Single -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.93	0.00			
	Other -	0.03	0.05	0.12	0.32	0.30	0.02	0.10	0.01	0.01	0.00	0.01	0.00	0.00	0.03	0.00			
		SHIB	010	3 mat	SNII	W.IDC	TOF	(SN)	42	ACH	alyrae	Inart	48th	MIRA	cini	lether	⊥ 0.0		
		Ċ	MIST	-)		5		5*			64.	40		م	ensisi	~			
								Predi	cted	labe	I			2.					

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Confusion Matrices (excluding class 99)

			_		Coi	nfusio	n Matr	ix - No	o Class	5 99: M	like &	Silogr	am				
	SNIa -	0.79	0.04	0.09	0.04	0.01	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	SNIa-91bg -	0.05	0.83	0.05	0.01	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	SNIax -	0.28	0.09	0.51	0.04	0.04	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.9
	SN-II -	0.17	0.02	0.16	0.42	0.03	0.18	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	- 0.6
	SN-lbc -	0.08	0.20	0.20	0.11	0.36	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
	TDE -	0.01	0.00	0.01	0.01	0.00	0.92	0.02	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	
e	SLSN-I -	0.01	0.00	0.01	0.07	0.01	0.01	0.89	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	- 0.6
e lab	KN -	0.00	0.02	0.00	0.01	0.02	0.01	0.00	0.95	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Tru	AGN -	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.97	0.00	0.00	0.00	0.00	0.00	0.00	
	RRlyrae -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.98	0.00	0.01	0.00	0.01	0.00	- 0.4
	Mdwarf -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.00	0.01	0.00	
	EBE -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	0.00	0.00	
	MIRA -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.96	0.03	0.00	- 0.2
	uLens-Single -	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.99	0.00	
	Other -	0.05	0.06	0.24	0.31	0.14	0.04	0.09	0.01	0.01	0.00	0.00	0.00	0.00	0.04	0.00	
		GN12	- 1p) wiat	(N-11	, hpc	TOF	SNI	t2	n CN	113e	Nart	EBH	NRA	, c	Je her	L 0.0
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Confusion Matrices (excluding class 99)

Combining the top solutions



The PLAsTiCC data



Unblinded Data Release for PLAsTiCC

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LSST Dark Energy Science Collaboration and the LSST Transients and Variable Stars Science Collaboration

https://plasticc.org/

https://doi.org/10.5281/z enodo.2535746

By the numbers

- More than 1 million new SEDs across several new models
- 15* classes in training set, one not represented in training
- ~ 3.5 million objects in test set w/ < 8000 objects for training
- ~ 450 million observations (LSST WFD + DDF) in 6 bands ~ 18.5 GB
- Even simplified, PLAsTiCC is the largest simulation of light curves the time-domain sky in the optical ever

Slide credit: Gautham Narayan

Thinking about PLAsTiCC 2.0

- Host-galaxy information
- Realistic photo-z
- Early classification
- Image based challenge

Summary

- 1094 teams have participated on Kaggle
- 18 models were simulated
- Data have already been used by many groups
- More work is needed to digest all the solutions

"KAGGLE IS ADDICTIVE !

ENTER AT YOUR OWN RISK !!!"

"PLASTICC IS ADDICTIVE !

ENTER AT YOUR OWN RISK !!!"